NAVAL POSTGRADUATE SCHOOL
Monterey, California

THESIS

THE ROLE OF COLOR AND FALSE COLOR IN OBJECT RECOGNITION WITH DEGRADED AND NON-DEGRADED IMAGES

by
Juan A. Aguilar Cavanillas

September 1999

Thesis Advisor: Williams K. Krebs
Second Reader: David H. Olwell

Approved for public release; distribution is unlimited.

REPORT DOCUMENTATION PAGE

Form Approved
OMB No. 0704-0188

1. AGENCY USE ONLY *(Leave blank)*	2. REPORT DATE	3. REPORT TYPE AND DATES COVERED
	September, 1999	Master's Thesis

4. TITLE AND SUBTITLE
THE ROLE OF COLOR AND FALSE COLOR IN OBJECT RECOGNITION WITH DEGRADED AND NON-DEGRADED IMAGES

5. FUNDING NUMBERS
N00173-99-WR-00215

6. AUTHOR(S)
Aguilar Cavanillas, Juan A.

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)
Naval Postgraduate School
Monterey, CA 93943-5000

8. PERFORMING ORGANIZATION REPORT NUMBER

9. SPONSORING / MONITORING AGENCY NAME(S) AND ADDRESS(ES)
Defense Advanced Research Projects Agency, Mr. Ray Balcerak, 3701 N. Fairfax Drive, Arlington, VA, 22203-1714

10. SPONSORING / MONITORING AGENCY REPORT NUMBER

11. SUPPLEMENTARY NOTES
The views expressed in this thesis are those of the author and do not reflect the official policy or position of the Department of Defense or the U.S. Government.

12a. DISTRIBUTION / AVAILABILITY STATEMENT
Approved for public release; distribution unlimited.

12b. DISTRIBUTION CODE

13. ABSTRACT *(maximum 200 words)*

Recent technological advances in the design and manufacturing of night vision multispectral sensors now allow spatially registered imagery provided by each of the sensors to be combined within a single fused image for display to an end user. The product is a multispectral false-colored rendering of the imaged scene. The use of false color in fused imagery may facilitate object recognition, providing contour information of the objects present in the scene, but incongruently colored fused imagery may be disruptive of perceptual performance. This study investigated if the use of false color imagery compared to natural color imagery was helpful or not in object recognition. Subjects' reaction times (RTs) and error rates were measured in a standard naming task. Stimuli consisted of photographs of food objects that had been manipulated in color (natural color, false color, natural grayscale, and false grayscale) and noise (three levels). The results of the experiment showed similar differences in RTs between color images (natural or false) and their grayscale counterparts at different levels of noise, indicating that both color conditions were similarly helpful in object recognition. These results give an indication that false color may be useful in multispectral sensors based on its facilitation of image segmentation with shape degraded images.

14. SUBJECT TERMS
Human Systems Interface, Sensors, Sensor Fusion, Target Recognition

15. NUMBER OF PAGES
110

16. PRICE CODE

17. SECURITY CLASSIFICATION OF REPORT	18. SECURITY CLASSIFICATION OF THIS PAGE	19. SECURITY CLASSIFI- CATION OF ABSTRACT	20. LIMITATION OF ABSTRACT
Unclassified	Unclassified	Unclassified	UL

NSN 7540-01-280-5500

Standard Form298(Rev.2-89)
Prescribed by ANSI Std. 239-18

THIS PAGE INTENTIONALLY LEFT BLANK

Approved for public release; distribution is unlimited.

THE ROLE OF COLOR AND FALSE COLOR IN OBJECT RECOGNITION WITH DEGRADED AND NON-DEGRADED IMAGES

Juan A. Aguilar Cavanillas
Lieutenant Commander, Spanish Navy

Submitted in partial fulfillment of the
requirements for the degree of

MASTER OF SCIENCE IN OPERATIONS RESEARCH

from the

NAVAL POSTGRADUATE SCHOOL
September 1999

Author: Juan A. Aguilar Cavanillas

Approved by: William K. Krebs, Thesis Advisor

Jason McCarley, Thesis Co-advisor

David H. Olwell, Second Reader

Richard E. Rosenthal, Chairman
Department of Operations Research

THIS PAGE INTENTIONALLY LEFT BLANK

ABSTRACT

Recent technological advances in the design and manufacturing of night vision multispectral sensors now allow spatially registered imagery provided by each of the sensors to be combined within a single fused image for display to an end user. The product is a multispectral false-colored rendering of the imaged scene. The use of false color in fused imagery may facilitate object recognition, providing contour information of the objects present in the scene, but incongruently colored fused imagery may be disruptive of perceptual performance. This study investigated if the use of false color imagery compared to natural color imagery was helpful or not in object recognition. Subjects' reaction times (RTs) and error rates were measured in a standard naming task. Stimuli consisted of photographs of food objects that had been manipulated in color (natural color, false color, natural grayscale, and false grayscale) and noise (three levels). The results of the experiment showed similar differences in RTs between color images (natural or false) and their grayscale counterparts at different levels of noise, indicating that both color conditions were similarly helpful in object recognition. These results give an indication that false color may be useful in multispectral sensors based on its facilitation of image segmentation with shape degraded images.

THIS PAGE INTENTIONALLY LEFT BLANK

TABLE OF CONTENTS

I. INTRODUCTION **1**

II. BACKGROUND **7**

A. HISTORY 7
B. PERCEPTION OF COLOR IN THE HUMAN VISUAL SYSTEM 8
1. Electromagnetic (EM) Spectrum *8*
2. Human Visual System *9*
C. CURRENT NIGHT VISION DEVICES 18
1. Image Intensifiers *19*
2. Thermal Infrared Devices *21*
D. MULTISPECTRAL IMAGE FUSION DEVICES 25
E. REVIEW OF THE LITERATURE 28
F. HYPOTHESIS 47

III. EXPERIMENT **51**

A. METHODS 51
1. Participants *51*
2. Apparatus *51*
3. Stimuli *52*
4. Procedure *55*
5. Experimental Design *57*
B. DEVELOPMENT OF THE STATISTICAL MODEL 58
C. RESULTS AND DISCUSSION 58

IV. CONCLUSIONS **79**

LIST OF REFERENCES **83**

INITIAL DISTRIBUTION LIST **89**

THIS PAGE INTENTIONALLY LEFT BLANK

LIST OF FIGURES

Figure 1: Spectral response of Eye, Image Intensifiers and IR Sensors. (MAWTS-1, 1995)....................10

Figure 2: Visible Color Spectrum. (Matlin & Foley, 1997)....................10

Figure 3: Wavelength Composition of Sunlight and Artificial Light. (Matlin & Foley, 1997)....................12

Figure 4: The Color Wheel, representing all the wavelengths of the visible light spectrum of the objects. (Matlin&Foley, 1997)....................12

Figure 5: Subtractive mixtures for blue paint and yellow paint.(Matlin & Foley, 1997)..14

Figure 6: Additive mixtures for blue light and yellow light. (Matlin & Foley, 1997).....14

Figure 7: Predicting additive mixtures. (Matlin & Foley, 1997)....................16

Figure 8: Absorption curves for the three cone pigments. (Matlin & Foley, 1997)....................16

Figure 9: Moonless Night Spectral Composition. (MAWTS-1, 1995)....................20

Figure 10: Diurnal Cycle Example. (NAWTS-1, 1995)....................23

Figure 11: Mean reaction times (msec) for each level of noise and color condition........60

Figure 12: Mean error rates (%) for each level of noise and color condition...............60

Figure 13: Reaction times color advantage (msec) for each level of noise and hue........64

Figure 14: Error rates color advantage (%) for each level of noise and hue................64

Figure 15: Mean reaction times (msec) for hue and color conditions....................68

Figure 16: Mean error rates (%) for hue and color conditions....................68

Figure 17: Mean reaction times (msec) for noise and color conditions....................69

Figure 18: Mean error rates (%) for noise and color conditions....................69

Figure 19: Mean reaction times (msec) for noise and hue conditions....................71

Figure 20: Mean error rates (%) for noise and hue conditions....................................71

LIST OF TABLES

Table 1: Object names.....53

Table 2: Mean values and standard deviations of luminance for each color format and level of noise in cd/m^2.....55

Table 3: Mean reaction times and standard errors (msec) for each level of noise and color condition.....59

Table 4: Mean error rates and standard errors (%) for each level of noise and color condition.....59

Table 5: Mean reaction time differences (msec) for each level of noise and hue.....63

Table 6: Mean error rate differences (%) for each level of noise and hue.....63

Table 7: Tukey's Method Paired Comparisons.....75

Table 8: Mean reaction times paired comparisons for each level of noise and color Format (Transformed data).....76

Table 9: Mean error rates paired comparisons for each level of noise and color Format (Transformed data).....76

Table 10: Summary of the results.....80

THIS PAGE INTENTIONALLY LEFT BLANK

LIST OF ACRONYMS

CRT	Cathode Ray Tube
EM	Electromagnetic
ER	Error rates
FC	False Color
FG	False Gray
FLIR	Forward Looking Infrared
HDD	Heads Down Display
HUD	Heads Up Display
HVS	Human Visual System
I^2	Image Intensifier
IR	Infrared
ITI	Intertrial Interval
LWIR	Low Wavelength Infrared
MAWTS	Marine Aviation Weapons and Tactics Squadron
NC	Natural Color
NG	Natural Gray
NVD	Night Vision Device
NVG	Night Vision Goggle
NVESD	Night Vision and Electronic Sensors Directorate
RGB	Red-Green-Blue
RT	Reaction Time
SD	Standard Deviation

THIS PAGE INTENTIONALLY LEFT BLANK

EXECUTIVE SUMMARY

Current night vision devices (NVD's) used in military operations, such as night vision goggles (NVG) and forward looking infrared (FLIR) systems, were designed to allow operations in low visibility conditions. New military tactics require demanding capabilities that current NVD's are just partially able to accomplish.

Infrared (IR) systems sense radiated energy detecting thermal differences between an object and its background. Image intensifier (I^2) sensors amplify reflected moonlight and starlight taking advantage of nighttime illumination conditions. Because of this response to widely separated wavebands within the electromagnetic (EM) spectrum, each sensor suffers disadvantages that the other does not, which can change depending on the atmospheric and environmental conditions. But, nevertheless, both current sensing modalities seem to be complementary. Accordingly, fusing the imagery originated in these two complementary sensors into a single display may result in equal or better operator performance compared to the two single band sensor imagery alone. This technique is known as dual-band sensor fusion.

Currently there is no field capacity to combine the best attributes of both sensors into a single fused image. Recent experimental advances in sensoring and data display have permitted good progress in real time image fusion and display of multispectral sensors in either monochrome or synthetic chromatic form.

The image processing challenge is to generate an intuitively meaningful color image on a display for a human viewer. Algorithms to perform this function in an optimum manner are currently under development. Since neither sensor is in the visible waveband, the artificial color mappings produced by some fusion algorithms will

generally produce false-color imagery whose chromatic characteristics do not correspond in any intuitive or obvious way to those of a scene viewed under natural photopic illumination. To the degree that human perception relies on stored knowledge of objects' chromatic characteristics, false color images may be disruptive of perceptual performance, making colored sensor fusion unhelpful in object recognition.

The reason for using color in fused imagery is based on the assumption that color (natural or artificial) facilitates image segmentation, providing contour information about the individual objects present in that scene as a way to achieve target detection. Past psychophysical research has been equivocal in determining what utility, if any, sensor fusion has for human performance. Research in this field has been inconclusive due to differing experimental methodologies used in these studies.

In order to measure the effectiveness of sensor fusion devices in enhancing the night capabilities of military operators over currently employed systems detailed exploration in the area of human factors was required.

The objective of this thesis was to quantitatively assess the role of natural and artificial color in object recognition when shape information is degraded, investigating whether and how false color might be useful in multi-band fused imagery. Digital photographs of natural objects (fruits and vegetables) were presented as natural and false color images, together with their gray scale counterparts, degraded by different levels of noise, and compared these imges in a standard naming task, trying to emulate imagery generated by multispectral devices. Two precise measures of visual ability that are critical to the military, reaction time (RT) and rate of accuracy in target detection, were measured.

Natural color might facilitate object recognition in either or both of two ways; by facilitating scene segmentation and by allowing access to stored color knowledge. In the presence of false colored images, recognition might be disrupted, because the access to stored knowledge is denied and participants would rely just in color contrast as a way to reach object recognition through scene segmentation. It was hypothesized that shorter RTs and greater accuracy rates would occur within the natural color images across all levels of noise and the difference in RTs between natural color and false color images would be largest in the conditions with the greatest amount of noise. The longest RTs and greatest error rates were expected within the grayscale images, because participants would not be able either to accomplish scene segmentation or to access stored knowledge during the object recognition task. Intermediate results would be achieved by false color images, due to the possibility at least to fulfill scene segmentation, originated by the presence of color.

As a result of the analysis conducted trying to assess the benefit of using color in object recognition, it can be concluded that both natural and false hue conditions resulted equally beneficial in the task accomplished during the experiment. There was no evidence of false color as a disruptive factor during this task, and both natural and false hue were similarly useful at different levels of image degradation. The reason for this conclusion is based on the assumption that participants conducted a bottom-up process during the object recognition task, making use of color (natural or false) to achieve image segmentation.

THIS PAGE INTENTIONALLY LEFT BLANK

ACKNOWLEDGEMENTS

The author would like to acknowledge and express appreciation to my thesis committee members, Professor William Krebs, Professor David Olwell and Dr. Jason McCarley, for their guidance and patience during the elaboration of this Thesis.

Special thanks to Dr. Michael Sinai. His assistance in providing the programming and ideas to conduct the Experiment significantly contributed to my ability to complete the work.

I. INTRODUCTION

Current night vision devices (NVDs) used in military operations, such as night vision goggles (NVG) and forward looking infrared (FLIR) systems, were designed to allow operations in low-visibility conditions. New military tactics require demanding capabilities that current NVDs are just partially able to accomplish. Greater target discrimination from decoys and background clutter is needed, together with greater display resolution, adequate magnification properties, and larger fields of view (Krebs, Scribner, Miller, Ogawa & Schuler, 1998; Marine Corps CDC, 1995). By combining information from multiple single-band sources within a unitary display, researchers hope to overcome perceptual limitations inherent in the images provided by various electro-optical sensors singly (Sinai, McCarley, Krebs & Essock, 1999a).

Infrared (IR) systems sense radiated energy detecting thermal differences between an object and its background. Image intensifier (I^2) sensors amplify reflected moonlight and starlight by taking advantage of nighttime illumination conditions. Because of this response to widely separated wavebands within the electromagnetic (EM) spectrum, each sensor maintains and suffers disadvantages that the other does not, which can change depending on the atmospheric and environmental conditions (Sinai et al., 1999a). For example, resolution is better in I^2 sensors, but contrast between heat-emitting objects and their surroundings can be better determined by IR sensors (Sinai et al., 1999a). Limitations in each of the sensing modalities can sometimes be disorienting by creating visual illusions (Crowley, Rash & Stephens, 1992), while alternating between these modalities can be difficult, confusing and distracting (Rabin & Wiley, 1994). Nevertheless, both current sensing modalities seem to be complementary. Accordingly, fusing the imagery originated in these two complementary sensors into a single display may result in equal to or better operator performance compared to the two single-band sensor imagery alone. This technique, known as dual-band sensor fusion, could also provide scene information not present in either single band image alone by deriving emergent information based on the difference between the sensors (Sinai et al., 1999a).

The contrast available in a fused image is often displayed as a monochrome or gray scale image (Therrien, Scrofani & Krebs, 1997; Peli, Peli, Ellis & Stahl, 1999). Techniques developed to introduce synthetic color to fused imagery (Scribner, Satyshur, Schuler & Kruer, 1996; Waxman, Gove, Seibert, Fay, Carrick, Racamato, Savoye, Burke, Reich, McGonagle & Craig, 1996; Scribner, Warren, Schuler, Satyshur & Kruer, 1998; Krebs, McCarley, Kozek, Miller, Sinai & Werblin,1999a), attempting to provide additional information through color contrast, are examples of the emergent information originated by sensor fusion.

For a human operator, the multiple sources of imagery need to be fused and displayed in a form that is easy and natural to interpret, improving the operator performance (Peli et al., 1999). Currently there is no field capacity to combine the best attributes of both sensors into a single fused image. Recent experimental advances in sensoring and data display have permitted good progress in real time image fusion and display of multispectral sensors in either monochrome or synthetic chromatic form (McDaniel, Scribner, Krebs, Warren, Ockman & McCarley, 1998).

The need is for new image processing techniques to combine the multispectral images so that the resultant image will have more information content than any of the original images, as it has been demonstrated by several researchers (Scribner et al., 1998; Krebs et al., 1999a; Therrien et al., 1997; Waxman, Aguilar, Fay, Ireland, Racamato, Ross, Carrick, Gaove, Seibert, Saboye, Reich, Burke, McGonagle & Craig, 1998). This requires studies in data formatting such as color-coding or object enhancements (e.g., towers hanging or power line for obstacle avoidance) (McDaniel et al., 1998). The image processing challenge is to generate an intuitively meaningful color image on a display for a human viewer that should improve the operator performance, facilitating discrimination of objects from backgrounds and situational awareness by means of scene segmentation.

Past psychophysical research has been equivocal in determining what utility, if any, sensor fusion has for human performance. While some studies have found a significant advantage for fused imagery over single sensor imagery (Essock et al., 1999a; Toet, Ijspeert, Waxman & Aguilar, 1997; Waxman et al., 1996), others have not (Steele and Perconti, 1997; Krebs et al., 1998; Essock, Sinai, McCarley, DeFord & Srinivasan, 1999b). These discrepant results can be attributed to the differences in fusion algorithms tested, and to the differences in the psychophysical tasks employed (Essock et al., 1999b). It is not so obvious that sensor fusion is going to be beneficial for perceptual performance (Sinai, McCarley & Krebs, 1999b).

Since neither sensor is in the visible waveband, the artificial color mappings produced by some fusion algorithms will generally produce false-color imagery whose chromatic characteristics do not correspond in any intuitive or obvious way to those of a scene viewed under natural photopic illumination. To the degree that human perception relies on stored knowledge of objects' chromatic characteristics, false color images may be disruptive of perceptual performance (Sinai et al., 1999b), making colored sensor fusion unhelpful in object recognition.

The reason for using color in fused imagery is based on the assumption that color (natural or artificial) facilitates image segmentation (Walls, 1942), providing contour information about the individual objects present in that scene as a way to achieve target detection. It should also be considered that the role of color in object recognition has not been determined clearly enough either. Past research in this field has been inconclusive due to differing experimental methodologies used in these studies. Several tasks and different types of stimuli were presented to the participants. Observers were required to recognize or identify natural or manufactured objects presented as colored or achromatic photographs, line drawings, artificially colored photographs, etc., using noise or blur as image degrading factors as a way to simulate poor resolution conditions (Wurm, Legge, Isenberg & Luebker, 1993; Ostergaard and Davidoff, 1985; Biederman and Ju, 1988; Joseph and Proffitt, 1996).

In order to measure the effectiveness of sensor fusion devices in enhancing the night capabilities of military operators over currently employed systems, detailed exploration in the area of human factors is required.

This thesis is focused on the human factors of sensor fusion; more specifically, human perception of natural and artificial color images similar to those produced by sensor fusion processes. The objective of this thesis is to quantitatively assess the role of natural and artificial color in object recognition when shape information is degraded, investigating whether and how false color might be useful in multi-band fused imagery. Digital photographs of natural objects (fruits and vegetables) were presented as natural and false color images, together with their gray scale counterparts, degraded by different levels of noise, and comparing them in a standard naming task, trying to emulate imagery generated by multispectral devices. Two precise measures of visual ability that are critical to the military, reaction time (RT) and rate of accuracy in target detection, were measured.

Natural color might facilitate object recognition in either or both of two ways; by facilitating scene segmentation (Walls, 1942) and by allowing access to stored color knowledge (Joseph and Proffitt, 1996). In the presence of false colored images, recognition may be disrupted, because the access to stored knowledge is denied and participants will rely just in color contrast as a way to reach object recognition through scene segmentation. It is hypothesized that shorter RTs and greater accuracy rates will occur within the natural color images across all levels of noise and the difference in RTs between natural color and false color images will be largest in the conditions with the greatest amount of noise. Faster RTs are expected within the natural color images because participants will use color information to access stored knowledge of the object's chromatic features, and they will be able also to fulfill scene segmentation. Larger effects of natural color images are also expected in the conditions with higher levels of noise because here, since the objects' shape information is degraded, subjects may be expected to rely more heavily on color information to recognize the stimuli. The longest RTs and greatest error rates are expected within the gray scale images, because participants will not be able either to accomplish scene segmentation or to access stored knowledge during the object recognition task. Intermediate results will be achieved by false color images, due to the possibility at least to fulfill scene segmentation, originated by the presence of color. If color is used only for scene segmentation similar effects of natural color and false color images are expected, although they should be faster and more accurate than the effects originated by the gray scale images.

II. BACKGROUND

A. HISTORY

The Vietnam War era witnessed the great expansion of the infrared industry. This industrial development was motivated by the inability of the U.S. forces to prevent North Vietnamese forces from conducting night operations (Schwarzkopf, 1992).

Since the post-Vietnamese era, all military high value platforms possess NVDs. These systems, that use specific sensors and techniques necessary to acquire and engage opposing forces during low visibility or nighttime periods under adverse warfare environments, have been proven effective in all kind of combat operations (NVESD, 1997). However, unanticipated problems have arisen while utilizing these devices. A human unaided perception of the surroundings at night is vastly different when observed with NVDs (Vargo, 1999). The user's lack of understanding of the night environment and its impact on the NVDs performance has caused the capabilities of these devices to be exceeded, resulting in numerous mishaps (Salvendy, 1997). Also, the increasing sophistication of military tactics and weapon systems require enhanced capabilities that current NVDs are not able to accomplish (Krebs et al., 1998). Multiband image fusion devices, currently under development, are supposed to solve several of the existing limitations of the infrared systems and to achieve the tasks required by modern nighttime warfare. In these new devices, the information provided by each of the sensors in the system is combined into a single fused image before being displayed to an end user. The resulting image is a multispectral false-colored rendering of the imaged scene. The expected advantage of fused images is not only choosing the most helpful effects of each of the fusioned sensors, but also obtaining additional information based on the difference between the sensors.

This study will investigate one of the unsolved problems of these new NVD's: the use of color in the resulting fused imagery. A generic presentation of how the human visual system (HVS) accomplishes the perception of color will provide a basic understanding of the problems related to adding color to multisensor fused systems. A general description and characteristics of single-band sensors currently in use are provided to aid in the comprehension of image fusion techniques and future multisensor devices. Previous research involving the role of color in object recognition is summarized, along with several studies that investigate and develop different techniques of color fusion.

B. PERCEPTION OF COLOR IN THE HUMAN VISUAL SYSTEM

1. Electromagnetic (EM) Spectrum

The first characteristic of the night environment relevant to an understanding of night vision technology is the EM spectrum of the night sky and its relationship to the eye and to the NVD's. NVD's allow us to exploit a greater portion of the EM spectrum as compared to the human eye. This issue can be seen in Fig. 1.

and to the NVD's. NVD's allow us to exploit a greater portion of the EM spectrum as compared to the human eye. This issue can be seen in Fig. 1.

The NVG's, FLIR, and most night imaging devices, including the human eye, are sensitive to different wavelengths of the EM spectrum. These frequency bands are similar in nature and their relationship can be clearly expressed by their position in the EM spectrum, shown in Fig. 2.

As it can be seen, the optical band covered by visible light is a relatively small portion of the entire spectrum. Visible and near IR light are considered to be reflected energy, while the thermal bands in the mid and far infrared are primarily radiated energy.

2. Human Visual System

The human visual system (HVS) is sensitive to radiation whose wavelength is in the 0.4 to 0.7 micron range of the EM spectrum. When a combination of these radiations reach the human eye, neural processing of these signals will originate a psychological reaction called color vision. Visible radiation received by the HVS may come directly from a light source, but is usually reflected by object surfaces before reaching our eyes.

Three primary perceptual dimensions of these radiations combine to define our psychological perception of color: hue (wavelength of the radiation), saturation (hue purity) and lightness (intensity of the light source).

Hue is the reaction to wavelengths ranging from 0.4 microns (violet) to 0.7 microns (red). As Newton demonstrated, white light really consists of a combination of

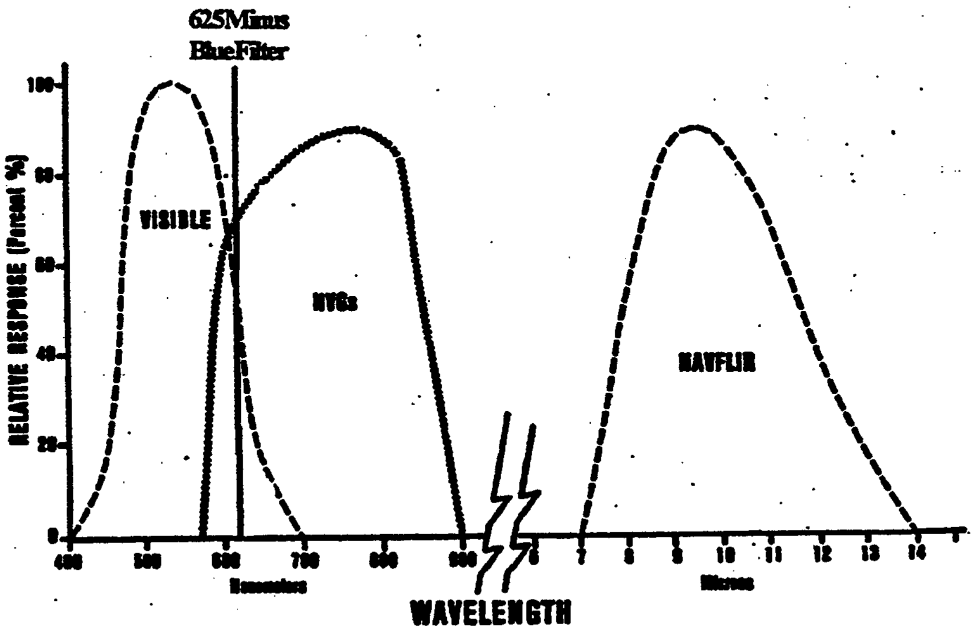

Figure 1: Spectral response of eye, image intensifiers and IR sensors (MAWTS-1, 1995)

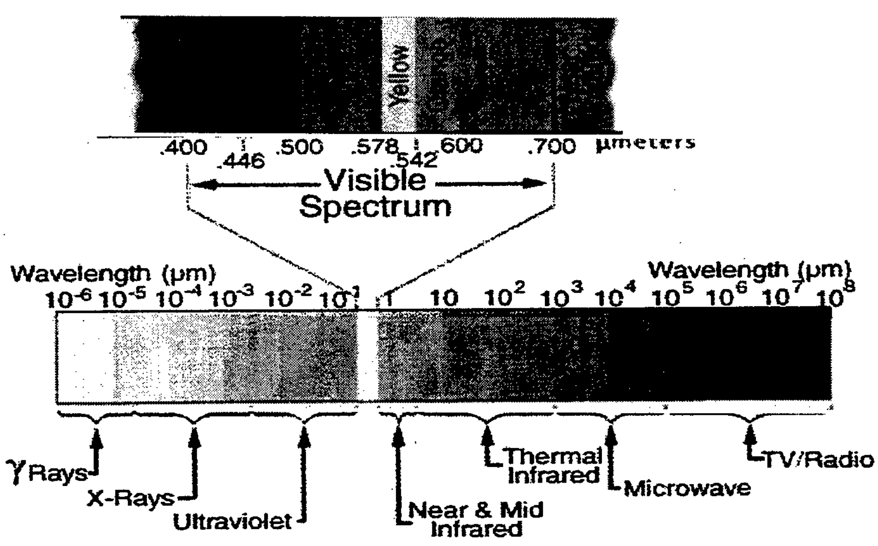

Figure 2: Visible Color Spectrum (Matlin & Foley, 1997)

different colored lights. Each wavelength included in this range after being processed by the HVS, produces the perception of a specific color, as it is shown in Fig. 3.

One way to organize colors, proposed by Newton in 1704, is in terms of a color wheel. The outside of the wheel represents monochromatic colors (those that can be produced by a single wavelength) plus non-spectral hues (those that cannot be described in terms of a single wavelength from the visual spectrum). Similar hues are located near one another.

In addition to hue, our experience of color is characterized by lightness and saturation. Objects vary in the amount of light they reflect from their surfaces. Lightness is the apparent reflectance of a color. It describes our psychological reaction to the physical characteristic, reflectance. Objects' lightness vary from very dark (black) to very light (white), with other shades of lightness in between (Matlin & Foley, 1997).

Another characteristic of color is saturation, our psychological reaction to the physical characteristic, purity. Saturation measures the amount of white light added to a hue. A saturated hue, lying on the perimeter of the color wheel, no white light added, is perceived as a deep hue. An unsaturated hue will be closer to the center of the wheel and is perceived as a much lighter hue. Completely unsaturated colors are called achromatic or neutral, and they are perceived as white, shades of gray and black, depending on their amount of lightness. These colors are represented in the center of the color wheel, as it is shown in Fig. 4.

The mixture of monochromatic hues produces the perception of the whole diversity of colors in the human visual spectrum. Hues can be mixed in two different

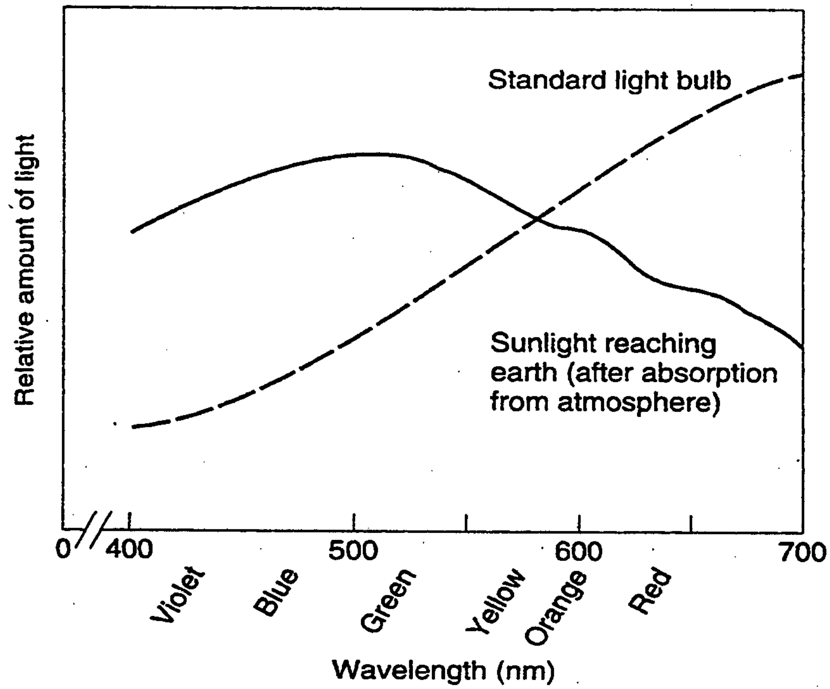

Figure 3: Wavelength composition of sunlight and artificial light. (Matlin & Foley, 1997).

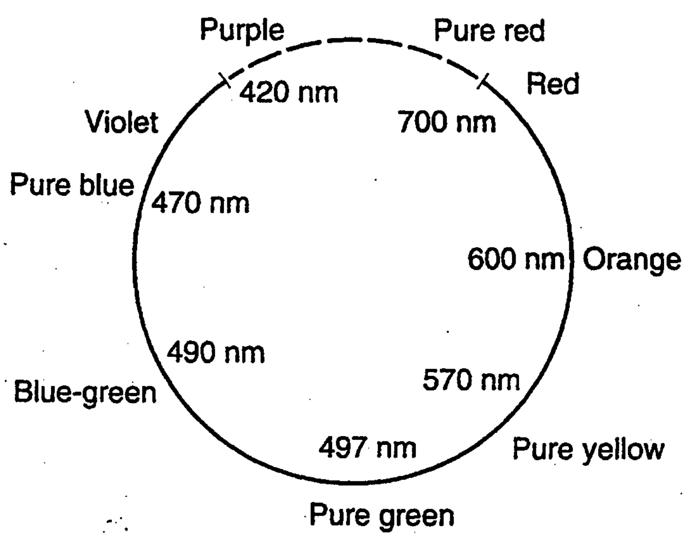

Figure 4: The color wheel, representing all the wavelengths of the visible light spectrum (Matlin & Foley, 1997).

ways. Subtractive mixing involves a single source that passes through filters or falls in pigments. Parts of the spectrum are absorbed or subtracted, as it is represented in Fig. 5. Additive mixture is accomplished by adding or combining colored lights of different wavelengths, as it is represented in Fig. 6. The result of color mixing can be predicted by using the color wheel. A graphic explanation of this method is shown in Fig. 7.

Color television is an example of additive mixtures. The screen consists of many tiny dots. When irradiated they glow blue, green or red. All different colors are produced by combination in our photoreceptors of the different lights generated in each screen dot when watched from an appropriated distance. A yellow patch is really composed of red and green dots (see Figure 4).

Hue wavelengths are not evenly arranged around the periphery of the wheel. This distribution is necessary to place complementary hues on exactly opposite sides of the color wheel. Complementary hues are those whose additive mixtures make an achromatic color (shade of gray).

By means of any of these two techniques, colored light reaches the human visual system (HVS), producing the perception of color. The way in which colored light produces the perception of color in the VHS is explained by two theories, each of them applied to different levels of the visual processing system. Trichromatic theory explains the way in which the input signal from the photoreceptors is combined (Neitz, Neitz & Jacobs, 1993). Opponent process theory explains how the information provided by the photoreceptors is interpreted by the neural system (DeValois & DeValois, 1975).

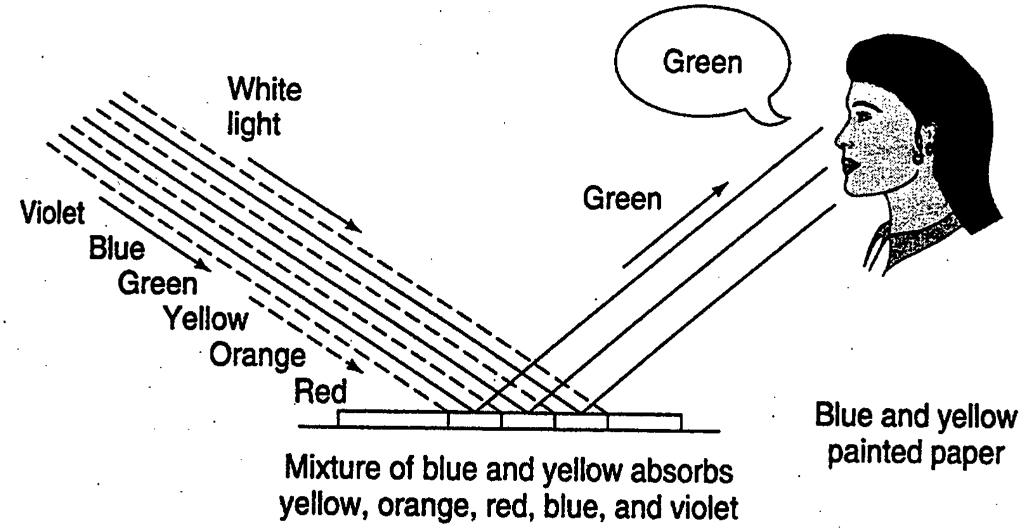

Figure 5: Subtractive mixtures for blue paint and yellow paint.

(Matlin & Foley, 1997)

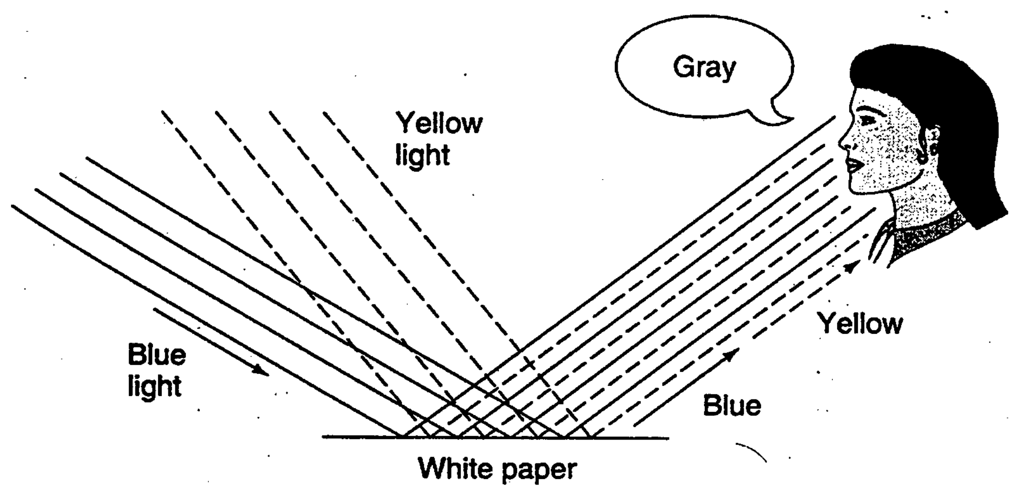

Figure 6: Additive mixtures for blue light and yellow light. (Matlin & Foley, 1997)

The Young-Helmholtz Trichromatic theory assumes that humans have three kinds of color receptors, each differentially sensitive to light from a different part of the visual spectrum. These receptors are called "cones" and they work best in well-lit environments, giving rise to the full range of colors (achromatic and chromatic). There is another kind of receptors in the human retina. These are the "rods," which work best in poorly lit environments where they give rise to the perception of achromatic colors.

Visual perception research has established that the three kinds of cone pigments have different but overlapping absorption curves (De Valois and De Valois, 1975), each of them being maximally sensitive to a different wavelength as it is shown in Fig. 8.

We will refer to these three kinds of cones as S (short wavelength), M (medium wavelength) and L (long wavelength) based on the wavelengths to which they are most sensitive. In this way, human visual receptors are able to distinguish the wavelength of an incoming signal, because it will activate one or several receptors in a unique pattern or distribution for each wavelength.

Trichromatic theory by itself cannot explain all the color phenomena. Some mechanism beyond the receptor level must combine the information from the cones in a complex way. Several pieces of evidence point to the existence of separate mechanisms for red, yellow, green and blue. How do these four mechanisms arise from only three cone systems? Human sense of color must arise from additional processing of the input from the three-cone system.

Opponent-process theory (De Valois & De Valois, 1975) covers this second level of visual processing system, beyond the photoreceptors. This process is implemented

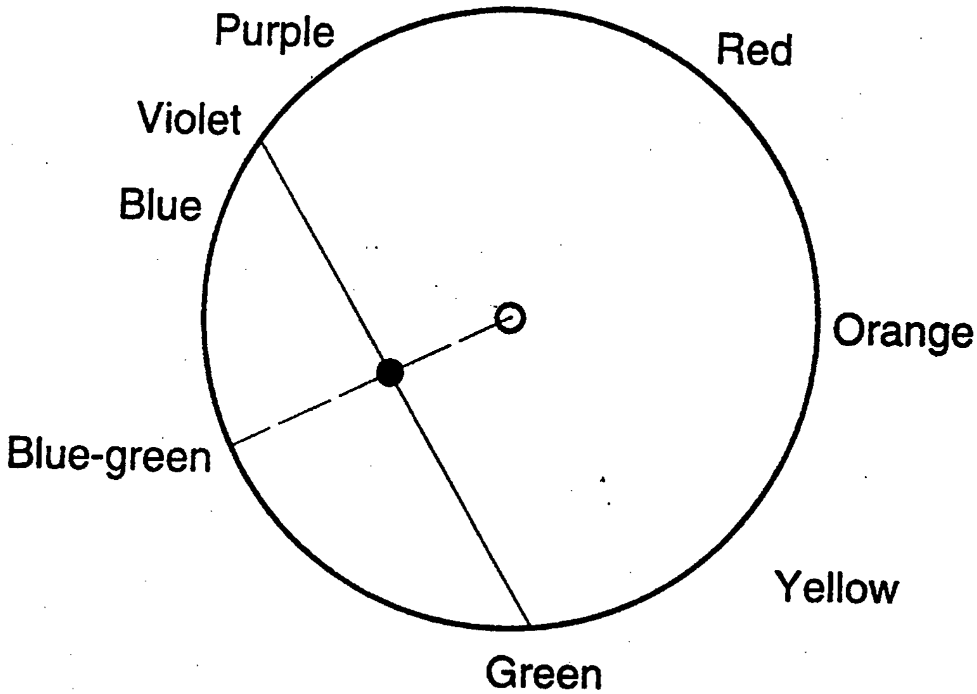

Figure 7: Predicting additive mixtures. (Matlin & Foley, 1997)

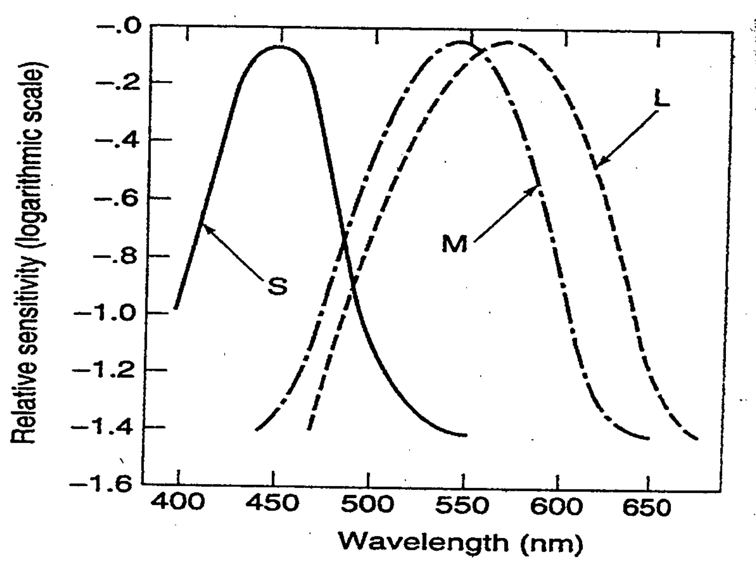

Figure 8: Absorption curves for the three cone pigments. (Matlin & Foley, 1997)

by means of the neural connectors among photoreceptors and neurons in the human retina. De Valois & De Valois (1975) modeled all these possible connections showing how both chromatic and achromatic information could be conveyed through identical mechanisms and it also illustrates how four color channels could arise from three cone systems (Matlin & Foley, 1997). This theory, whose development is far beyond the scope of this thesis, is basic in the development of several fusion algorithms (Waxman, Fay, Gove, Seibert, Racamato, Carrick & Savoye, 1995).

Another characteristic of color is color constancy. Because of color constancy, humans tend to see the hue of an object as staying the same despite changes in the wavelength of the light illuminating the object. Variations in illumination light may arise by changes in the intensity or in the composition of the illumination source. Absolute color constancy would be obtained if an object appeared to be the same color regardless of the type of illumination or the colors of nearby objects (Maloney, 1993). Our perception of color, then, is not dependent on the absolute wavelengths reaching our retinas, but on reflectance relationships among objects in our field of vision (Brou, Sciascis, Lindeln & Lettvyn, 1986). Color constancy is probably not maintained completely. So, human color perceptions are influenced to a degree by the nature of the illumination. This lack of consistency for the intensity of reflected light required the HVS to develop a variety of mechanisms to disentangle the contradictions of varying illumination and thereby to achieve nearly constant color perception based on distal surface reflectivity (Matlin & Foley, 1997). Based on this characteristic of the HVS, color constancy seldom breaks down to the extent that an observer would assign two different color names to the same object just because of changes in illumination (Jameson & Hurvich, 1989). When an object is seen under different illumination conditions, it might look slightly different, but it will still be recognized as the same color. A major limitation to sensor fusion systems is that these mechanisms cannot be duplicated to achieve the same constant color perception.

C. CURRENT NIGHT VISION DEVICES

Night vision devices (NVDs) enable exploitation of the night environment by the NVD user by processing EM bands outside the human visual spectrum. These devices do not allow perfect vision during nighttime operations, but they do enable humans to improve their performance in multiple tasks such as movement on foot or even night attacks using sophisticated weapon systems, both land based or airborne.

Current military night operations are enabled through imaging in the visible-near infrared band (wavelengths of .57 to .9 microns) and in the thermal infrared band (wavelengths of 7 to 14 microns). Fig. 1 shows the portions of the EM spectrum covered by NVDs. Both types of NVD's are explained in more detail in the two next subsections.

1. Image Intensifiers

Image intensifiers (I^2) process the visible and near-infrared spectrum and, much like the human visual system, depend almost entirely on reflected energy from scene illumination (MAWTS-1, 1995). They amplify reflected moonlight and starlight (primarily yellow through near infrared light, with wavelengths of 0.57 to 0.9 microns) and ambient light produced by artificial sources of illumination (visible light wavelength of 0.4 to 0.7 microns).

Visible and near-infrared imagery is currently provided by the third generation of I^2 tubes. The five major components of an I^2 tube are the objective lens, the photo cathode, the microchannel plate, the phosphor screen and the eyepiece lens. Radiant or reflected optical energy received at this device is focused, turned into electric energy, amplified and turned again into green –yellow light in the 0.56 microns range, matching the peak sensitivity of photopic human vision. Finally it is inverted and focused before reaching the operator eye. Image intensified imagery is usually displayed in night vision goggles (NVG's).

The ratio of the brightness of the image at the output of the eyepiece lens over the luminance of the light entering the objective lens is called the gain of the I^2 tube. The variants of the Gen III NVG's currently used have a gain of 25,000, a substantial advantage for the unaided human eye in the night environment (MAWTS-1, 1995).

Illumination, expressed in lumens per square meter (lm/m^2) or lux, measures the amount of visual energy that exists in a specific location. Lunar illumination is the primary energy source for natural illumination in the night sky (MAWTS-1, 1995). Additionally, stellar phenomena and starlight provide certain amount of illumination. Figure 9 shows how moonless night sky illumination almost matches the peak sensitivity of NVGs.

Two other contributors of illumination are the sun and artificial sources. The setting sun at zero degrees below the horizon is too bright for NVG operations, however, approximately one half hour after sunset, when the sun has lowered to seven degrees below the horizon, it may provide useable illumination until it has set past twelve degrees. Artificial lighting such as street lights or radio tower warning lights can also provide significant illumination, but large concentrations of artificial illuminators can wash out the NVG image.

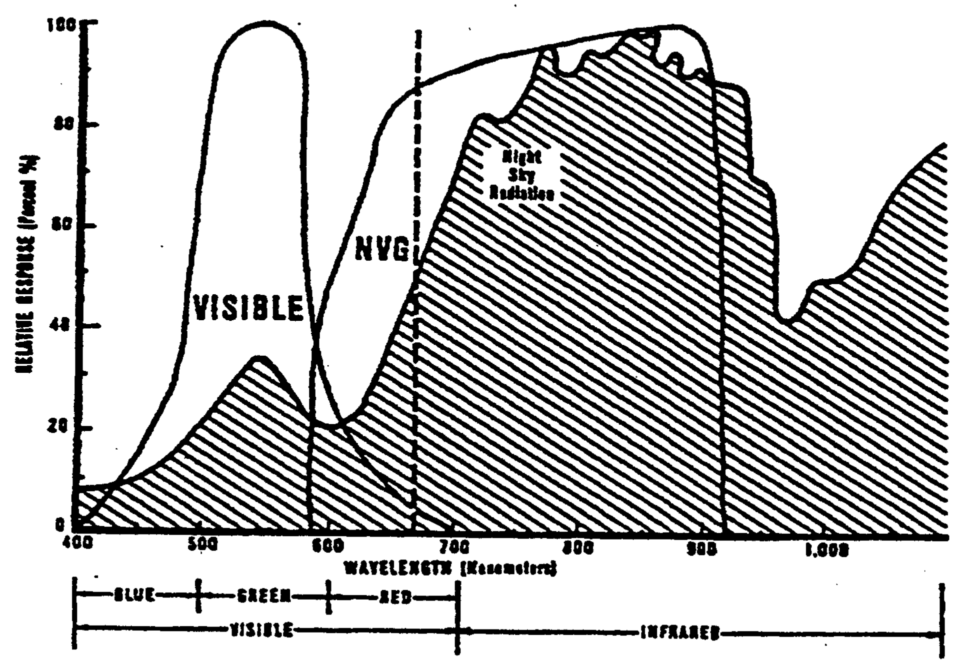

Figure 9: Moonless night spectral composition (MAWTS-1, 1995)

The atmosphere is the most important environmental factor controlling the performance of the NVGs. The atmosphere can attenuate the light, reducing the level of energy reaching the NVGs. This attenuation can occur by absorption or scattering mainly due to the fact that attenuation by refraction is almost negligible. NVGs operate by intensifying light energy between 625 to 960 nanometers. Any attenuation, either before or after it strikes the terrain, will effectively reduce the usable light available to the NVG and thus affect the resulting image. Attenuation is caused by impact of light particles with particles larger than one micron in length such as water vapor, dust, snow, and other natural or man-made obscurants. The effect of these particles will depend very much on their size and density, but all of them will affect distance estimation and depth perception reducing significantly the usefulness of these devices and even making them almost useless during adverse atmospheric conditions (MAWTS-1, 1995).

2. Thermal Infrared Devices

The thermal infrared devices, supported by several kinds of forward-looking infrared (FLIR) imaging devices, convert invisible thermal energy from the far infrared spectrum into a visible image. FLIR's generally process emissions from two infrared bands, midwave (3 to 5 microns) and long wave (8 to 12 microns). Infrared energy (thermal energy) within these bandwidths is emitted by all objects with a temperature above absolute zero (-273 degrees Celsius).

Natural thermal energy is produced when objects that have previously absorbed thermal energy from IR sources, such as the sun or warm air currents, start radiating this energy. Another source of thermal energy is from man-made objects such as the heat radiated as a result of the friction from moving parts in mechanical devices (MAWTS-1, 1995). It is important to note that most man-made objects emit in the 8 to 12 micron band, hence the military interest in LWIR sensors (Sampson, 1996).

In order to measure the thermal energy radiated by an object we define emissivity (E) as the ratio of an object's ability to emit thermal energy at a certain temperature over that of a black body at the same temperature. "Blackbody" is defined as the perfect absorber of thermal energy and therefore also a perfect emitter, with an efficiency of unity (MAWTS-1, 1995). Other factors impacting emissivity are material composition, ambient temperature and the object's temperature and geometry. Most natural objects have a high emissivity and therefore a majority of their thermal signature is from self-emission. Conversely, objects with low emissivity have a corresponding high reflectivity and therefore reflect thermal energy of their surroundings.

Thermal energy emitted by an object, whether it is internally generated or reflected by another source, determines its thermal signature. It is primarily the difference among thermal signatures of objects that defines the thermal scene (Sampson, 1996). An important measure of performance of a FLIR is "delta T" or the temperature difference of an object and its background (MAWTS-1, 1995). The cyclic heating and cooling of the terrain causes the diurnal cycle of temperature differences between objects of different thermal mass and inertia.

Figure 10 shows the diurnal cycle of temperature differences for an armored vehicle and the background terrain. From the graph one can visualize the negative thermal contrast (object cooler than background) of the armored vehicle on a clear sunny day and the positive thermal contrast (object warmer than background) of the armored vehicle at night. Because of the positive thermal contrast, FLIR's will be able to detect targets against the background during night periods.

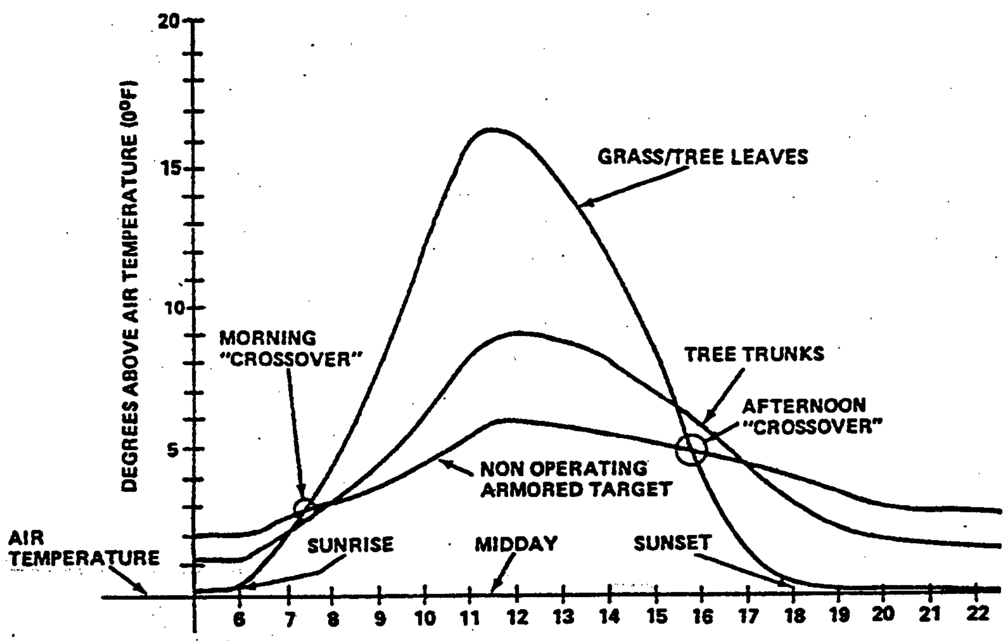

Figure 10: Diurnal cycle example (MAWTS-1, 1995)

Attenuation of thermal energy after it leaves its source can occur by absorption or scattering. Atmospheric vapor or humidity is the most significant absorber of thermal energy. In very hot and humid climates, the high amount of absorption may literally render the FLIR useless (MAWTS-1, 1995). Molecular scattering occurs when thermal energy particles strike other particles present in the atmosphere, as nitrogen, oxygen, water vapor and carbon dioxide. Because of these strikes, thermal energy can be scattered in different directions making it difficult to reach the IR sensor (MAWTS-1, 1995).

FLIR systems are complex and their detailed composition is far beyond the scope of this thesis. The basic elements of this device are the infrared sensor, the signal processor and the display unit. The detector array is composed of semiconductive material, which turns 8 to 12 microns heat energy into analog electrical output to the signal processor. The signal processor provides the special signal functions required to stabilize and enhance the analog output from the detector array. The signal from the processor is transformed to an image through the use of a cathode ray tube (CRT) and displayed on a "heads down display" (HDD), cockpit "heads up display" (HUD) or "helmet mounted display" (HMD) (MAWTS-1, 1995). Current FLIR technology is centered on the first generation (Gen I) FLIR thermal imaging device. The U.S. Army began integration of second generation FLIR's into new and existing weapon systems to maximize U.S. forces advantage on the battlefield (NVESD, 1997). IR imagery is displayed using a variety of forward looking infrared (FLIR) imaging devices (both scanners and IR focal plane arrays) displayed on monochrome phosphor monitors, the cockpit heads-up display, or combiner optics.

D. MULTISPECTRAL IMAGE FUSION DEVICES

The two sensing modalities currently used for night vision purposes (I^2 and IR) have been improved due to increases in sensor detection ranges and display resolution, but they still have their own limitations. I^2 devices need reflected light for detection and IR devices must be able to detect thermal contrasts among the objects in the scene (Vargo, 99). Recent advances in signal processing have permitted the possibility of combining the best attributes of the emissive radiation sensed by the thermal sensor and the reflected radiation sensed by the image intensifier sensor into a single "fused" image (Steele and Perconti, 1997).

Long wave IR and I^2 sensors are good candidates for image fusion. The thermal contrast between relatively high emissivity objects and the background is a good indicator of potential targets, obstacles and waypoints. The inability to see details in areas that have relatively poor thermal contrast, caused by low emissivity differences, might be greatly compensated for by fusing with an I^2 sensor. Given the proper illumination conditions, the "visible" contrast can provide very useful cues that are independent of thermal conditions. I^2 sensors might also aid in producing a natural representation of the scene due to the proximity of this wave band to that of the visible (0.4 to 0.7 microns) waveband (Steele and Perconti, 1997).

Recent technological advances in the production of multi-spectral sensors now allows I^2 and IR imagery to be mapped to a high speed processor where it can be fused and displayed to an end user (McDaniel et al., 1998). Some advantages of combining multiple spectral imagery into a single display might be: (a) reduced cost, space, computational processing and weight requirements form combined resources, (b) reduced operator workload by limiting the need to alternate between the two sensors, (c) improved object search, detection and recognition.

Numerous fusion techniques have been developed during the last years that produce both monochromatic and color imagery (Toet, van Ruyven & Valeton, 1989; Scribner, Satyshur & Kruer, 1993; Palmer, Ryan, Tinkler & Creswick, 1993; Toet & Walraven, 1996;Therrien et al., 1997; Waxman, Gove, Fay, Racamato, Carrick, Seibert & Savoye, 1997). All these techniques may differ on the algorithm approach but they all have the same objective: improving the image quality for the observer (Krebs, Scribner, McCarley, Ogawa & Sinai, 1999b).

A typical color fusion process transforms the dual monochrome bands generated at the I^2 and IR sensors onto display variables such as the red-green-blue (RGB) channels (based on human trichromatic vision theory) and opponent color processing (Waxman et al., 1997). This approach takes advantage of the observer's color vision system to introduce additional dimensionality for interpretation through color contrast. The use of color in image fusion was frequently advocated under the argument that color contrast can provide improved detection performance when added to luminance contrast (Peli et al., 1999).

If the final result of a fusion process is presented in a monochromatic format, the whole capability of the HVS is not being optimally used. Objects viewed by low-light and infrared sensors will generally have the same spatial characteristics, but they will have completely different contrast levels. By displaying these variations as color differences, as a result of sensor fusion techniques, target-background contrast should be improved and the dynamic range of the scene should be increased (Krebs et al., 1998).

There is a very important distinction between a color scene observed by the unaided eye through the HVS and a processed color fused image. The color mapping process is affected by the specific information provided by the two sensors. Since neither sensor is in the visible waveband, the color algorithms used may not produce imagery that matches the colors seen by the HVS (Steele and Perconti, 1997).

It is difficult to assume how beneficial multisensored colored images are going to be for human performance. Some experimental evidence indicates that object recognition depends on stored color knowledge of object's chromatic characteristics (Joseph & Proffitt, 1986), therefore, incongruency of false color images may be disruptive of perceptual performance, and could even produce worse performance compared to single-band imagery alone (Sinai et al., 1999a), although overall evidence is equivocal as to what role color plays in object recognition.

Another major limitation to sensor fusion systems is that HVS mechanisms cannot be duplicated to achieve color constancy, as it was previously stated in the HVS section. Therefore, varying illumination conditions will originate different chromatic representations of the same object. As it was stated above, past psychophysical research has been inconclusive in determining what is the role of color in human visual system and therefore, in determining what utility if any color sensor fusion has for human performance. A review of the literature might clarify which is the current situation in this field that has intrigued vision researchers for many years.

E. REVIEW OF THE LITERATURE

It is likely that color vision evolved in response to the changes of human behavior, during the process of adaptation to the natural environment. In Polyak's view, color vision evolved to facilitate food gathering, involving search and recognition of natural objects (Polyak, 1957). Color might facilitate these tasks by means of scene segmentation. Walls suggested that color promotes the perception of contour (Walls, 1942). Color differences, like luminance differences, can be used to segment images into regions containing information about individual objects and provide more reliable information about object shape, because shadows also produce luminance contours (De Valois & Switkes, 1983).

Color may also serve another perceptual function apart from scene segmentation: object recognition. Although virtually no object can be recognized on the basis of its color alone, the colors of some objects are less arbitrary than others, therefore objects with higher color diagnosticity, could be recognized in a faster way (Biederman & Ju, 1988).

Object recognition can be achieved by means of two different processes, both separately or in a combined way. During a bottom-up process, color is used to define the contour or shape of the objects present in a scene. Once the shape of the object is defined, human memory recognizes the object based on that contour. This is normally the case of objects with low color diagnosticity. On the other hand, during a top-down process, color is used to access memory in a direct way, and allows subjects to distinguish an object among others of similar shape, just based on its color. This is the case of objects with high color diagnosticity.

Assuming that scene segmentation is a bottom-up process, it should not depend on our knowledge of the colors of things. Diagnosticity, on the other hand, relies on memory. It might improve object recognition by restricting the set of possible alternatives (Wurm et al., 1993).

There is disagreement, however, as to whether or not color is actually used to facilitate object recognition (Wurm et al., 1993). This disagreement can be attributed to several causes including differences in psychophysical tasks employed, differences in luminance characteristics across the color conditions, the use of different levels of shape degradation, and differences in types of objects used as stimuli and color formats employed.

Three tasks have typically been used to determine the role of color in object recognition. These tasks are classification, verification and naming. In a classification task, participants are shown pictures or words that refer to a specific predesignated category (Price & Humphreys, 1989). In a verification task, a target name is presented to the participants and they must answer whether a subsequently presented stimulus matches the target or not (Ostergaard & Davidoff, 1985; Biederman & Ju, 1988; Joseph & Proffitt, 1996). During naming tasks, participants must verbally identify the object shown in each stimulus (Ostergaard & Davidoff, 1985; Biederman & Ju, 1988; Price & Humphreys, 1989; Wurm et al., 1993).

Discrepancies in the results of previous research studies were analyzed by their own authors. Price & Humphreys (1989) stated that surface information may affect object naming more strongly than classification, and that the effects of naming may be most pronounced on objects that require most differentiation, because extra time is then required to differentiate any given object from its structurally related competitors. Joseph & Proffitt (1996) argued that their results differed from those of other studies for many of the same reasons that Price & Humphreys's results differed. Because the objects they used in their verification tasks generally came from structurally similar categories (animals, fruits, vegetables, and flowers), that were also natural categories, it was not surprising to find an effect of surface color in their verification task.

Other aspects that may originate discrepant results in color research will be considered in more detail in this section while accomplishing the literature review.

Markoff (1972) measured reaction times (RTs) for subjects to decide which of three targets (tank, jeep or soldier) was present in a black-and-white or color slide. The targets were hidden in real-world backgrounds. He blurred the slides to evaluate the interaction of spatial resolution and color. He found that RTs were shorter (and error rates lower) for the color slides, and the advantage of color over black-and –white performance increased with great blur. These results indicate that color is helpful in a search task and that color may be more helpful when shape information is degraded.

Ostergaard and Davidoff (1985) investigated the role of color in the recognition and naming of everyday objects. Their study was based on the idea that color is unhelpful in shape processing, due to the considerable evidence for the separate processing of color and shape shown by anatomical and physiological research. Observations in monkeys indicate that the primate visual system consists of several separate and independent subdivisions that analyze different aspects of the same retinal image as color, depth, movement, and orientation. Human perceptual experiments are remarkably consistent with these predictions (Livingstone & Hubel, 1988). Therefore, they tried to find out at which stage of the object recognition process color and shape information combined, given that we are aware at the end of this process if objects are incongruently colored (Perlmutter, 1980). This means that color is not a part of the pictorial coding of objects, i.e., it is not necessary in order to describe the psychological description of the object, but rather it is stored as part of a set of attributes as depth, movement or orientation (Seymour, 1979). They hypothesized that any benefit from having color vision should be obtained from a later stage than identification (Ostergaard and Davidoff, 1985).

The first experiment considered the role of color in object naming, because if color affects the processing of objects at any stage from early registration to the availability of the object name, this should be reflected in the object naming latencies. Twenty-four common fruits and vegetables were photographed on black-and-white and color film. Each participant was shown the complete series of pictures and was required to name the objects depicted in those pictures. Colored pictures produced significantly faster response latencies than black-and-white pictures. Therefore, the authors concluded that color information is beneficial in object naming, although it was not clear whether those results occurred because color simply provides a separate cue for discriminating stimulus items, as part of a bottom-up process.

In the second experiment they tried to solve this problem by only using items of identical color and thereby removing the possibility of using color to discriminate between alternatives. They compared object naming directly to object verification with three types of stimuli: items depicted in their natural color (always red), achromatic versions, and items depicted in an inappropriate color (always blue). This final condition was included to determine whether an inappropriate color would be interfering or merely have the same effect as no color. In the naming task, participants were required to name the depicted objects as quick as possible without making errors. In the verification task participants were required to respond positively when the target item was presented. Before each block of trials, the participants were informed what color the stimuli would be and they were shown the three alternative items. Color effect reached significance in the naming task, but it failed to reach significance in the object verification task. The naming advantage found for red pictures of objects could not be attributed to the stimulus characteristics of the colors used, so they concluded that it should be due to the meaningful conjunction of color and shape. They also concluded that there was no detrimental effect of wrong color compared to achromatic input (Ostergaard and Davidoff, 1985).

The third experiment was run to verify the generality of the results of the previous one. In Experiment 2, the stimuli were blocked according to color type. In this experiment, correctly colored, inappropriate colored and achromatic stimuli were presented at random. Again, the participants accomplished naming and verification tasks. Positive responses during the verification task were significantly faster than negative responses. All other factors and interactions failed to reach significance. Item color was found to be significant in the naming task. Paired comparisons revealed that correctly colored pictures were named significantly faster than either achromatic or inappropriately colored versions. There was no significant difference between achromatic and inappropriate versions. Thus, the major result of Experiment 2 was confirmed.

These results show that color facilitates object naming but not object recognition. They found faster object naming for color than black-and-white pictures, and they believed this could be explained by assuming that objects are listed in semantic representation as a collection of physical attributes. One of these attributes is color, and they postulated that this attribute could be accessed directly by the physical color input. Another important conclusion of this study was that although correct color produced facilitation of object naming, inappropriate color did not cause significant inhibition in either Experiment 2 or 3.

Beiderman and Ju (1988) investigated the role of color in object recognition, comparing the latency at which objects could be named or verified when they were shown either as line drawings or color photographs. The empirical issue of this study was to determine if the presence of surface attributes of an object, such as color, facilitates the psychological representation of that object, over what can be simply derived by depiction of the object's edges. Color diagnosticity among objects was also investigated trying to determine whether color and brightness were providing a contribution to recognition independent of the main effect of photo versus drawings. For some kinds of objects, color is diagnostic of the object's identity. For other kinds, normally man-made objects, color is not diagnostic. If color was contributing to object recognition, then it should be found that the former kinds of objects should benefit more than the non-diagnostic objects by their depiction as color photographs rather than as line drawings.

It was expected that participants' reaction times and error rates for the naming task would be smaller for color stimuli. In the verification task, each presentation was shown in one of three different exposure times followed by a mask. The exposure times were 50, 65 and 100 milliseconds in duration. In this task participants could anticipate the surface characteristics of almost all of the targets, and for the diagnostic objects, the color as well. Therefore, if participants were using the color to access an object mental representation, then objects photographed in color or those that were diagnostic should be recognized faster relative to the naming tasks. It was also assumed that longer exposure duration and slightly dimmer projector intensity would favor colored photography (Biederman and Ju, 1988).

The results of the experiments did not match the authors's assumptions. Over the five experiments, mean RTs and error rates for naming or verifying line drawings were virtually identical to those for color slides. Even objects with diagnostic colors did not enjoy any advantage when presented as color slides during the verification task. They found a mean advantage favorable for the line drawings and also favorable for the objects with no diagnostic color. The conclusion for these studies was that a simple line drawing could be identified about as quickly and as accurately as a colored photographic image of that same object. Color diagnosticity did not facilitate object recognition. These results support the premise that the access to a mental representation of an object can be accomplished with an edge-based representation of a few simple components. Color plays only a secondary role in recognition when edges can be readily extracted (Biederman and Ju, 1988).

In contrast to Biederman's results, some authors speculated that surface characteristics should facilitate recognition. Following this line, Price and Humphreys (1989) examined the effects of color congruency and photographic detail on the naming and classification of objects from structurally similar and structurally dissimilar categories. Color congruency was also assessed by contrasting performance with correctly colored line drawings of objects, black-and-white outline drawings and line drawings assigned very incongruent colors.

To clarify all these effects, the authors conducted a series of experiments in which participants performed naming, subordinate (only with stimuli from structurally similar categories) and superordinate classification tasks. Color, when present, was part of the surface description of objects in Experiments 1 and 2. The influence of color in participants' performance as part of the object's surface description was examined in Experiment 3 by testing the effects of colored backgrounds on object naming (Price and Humphreys, 1989).

Price and Humphreys hypothesized that object color and surface details would be beneficial for discriminating between categorical members, because these objects require greater differentiation to separate the target object from competitors of the same category during a naming task. Their findings supported this hypothesis and revealed that the influence of surface color in object recognition is not only reserved for naming tasks. Classification of objects can also benefit from the use of congruent surface color when shape information is not sufficient for discriminating among category members. The implication of Price and Humphreys's findings is that effects of surface color are not necessarily reserved for the later, name-retrieval stages of processing (Joseph and Proffitt, 1996).

Joseph and Proffitt (1996) conducted a series of experiments to determine the influence of color as a surface feature, i.e., its role during a bottom-up process, versus its influence accessing stored knowledge during a top-down process, in order to achieve object recognition. They defined stored color knowledge as semantic information about the prototypical colors of objects, such as the knowledge that apples are typically red.

They considered that the role of stored knowledge of color in object recognition had not been examined deeply enough in previous studies. They also considered that the findings in the literature, concerning the role of color in object recognition, have yielded mixed results. They argued that for surface color to be a useful cue for recognition, the participant must decide if the surface color is appropriate for an object. Therefore, they would have to access an object's semantic description for this check process to occur and compare it with the surface color present in the image. This study investigated whether the decision that the stimulus matches the target or not, depends more on the activation of stored knowledge or on the processing of surface color.

Joseph and Proffitt conducted three experiments to investigate the roles of surface color and stored color knowledge in object recognition. Pictures of natural objects were used as stimuli because most of natural objects have prototypical colors as opposed to man-made objects in which color is quite more arbitrary. In this way they could measure the influence of color, when participants were presented natural objects showing completely different colors from those stored in their memories. According to the results of the first experiment, congruent surface color made recognition easier than did incongruent color, with a verification task. Congruently or incongruently colored line drawings of common natural objects were presented briefly, masked, then followed by a label. An object is considered congruently colored when it is showing the most prototypical color, that is the one that the vast majority of people have stored in memory as related to that specific object. These results appeared to conflict with Biederman and Ju's (1988) findings, but the authors argued that the reason for this discrepancy might be the different natures of the stimulus sets. Thus, use of surface color as a cue for recognition is more beneficial for objects from natural categories (Joseph and Proffitt, 1996).

Results from the second and third experiments confirmed their hypothesis. They concluded that the processing of shape information was more influential than any source of color information in object recognition, but when response interference could not be attributed to shape information, i.e., when both stimulus and target had similar shape, stored color knowledge was an overriding factor relative to surface color. They also found that the activation of stored color knowledge did not depend on the presence of surface color, because even the identification of uncolored pictures was affected by stored color knowledge. They examined the effect of stored color knowledge by observing RTs and error interference when semantic associations of color were present or absent. For example, an uncolored picture of an apple might have been followed by the label cherry or by the label blueberry. More interference should occur with the label cherry because apples and cherries share a prototypical color. Apples and blueberries are different in prototypical color and, therefore, interference should be less (Joseph and Proffitt, 1996).

Wurm, Legge, Isenberg, and Luebker (1993) investigated the role of color in object recognition trying to find out if color facilitates recognition in images with low spatial resolution. Previous studies have concluded (Markoff, 1972, Ostergaard and Davidoff, 1985, Biederman and Ju, 1988) that color improves object recognition more, when spatial resolution is low (blur or noise) or when shape information is less specific (fruits and vegetables vs. man-made objects). The major purpose of this research was to examine the hypothesis that color and shape information interact in object recognition, that is, color facilitates object recognition more when spatial resolution is low.

In their two main experiments, participants were presented full-color and gray-scale images of twenty-one different food items and vegetables. They chose to use food objects because they have a wide range of colors and shapes, so they were representative of natural objects. These objects may provide a favorable domain for revealing a role of color, given that color vision probably evolved in response to functional interaction with natural objects (Polyak, 1957).

The authors considered luminance as a factor that could have led to disagreement among the results of earlier studies examining the role of color in object recognition. Luminance characteristics varied across the color conditions in several of previous studies. In Markoff (1972) and Ostergaard & Davidoff (1985) studies, the distributions of luminance were not matched in the color and black-and-white slides. Biederman and Ju (1988) compared line drawings with color photographs. Visual analysis of the color photographs may have been disadvantageous, because of greater difficulty in edge extraction compared with line drawings (Wurm et al., 1996). To avoid this problem, Wurm and colleagues employed only gray-scale images matched pixel by pixel in luminance with the color images.

Wurm, Legge, Isenberg and Luebker (1993) were also interested in examining if color and shape information interact in object recognition, such that color facilitates recognition more when spatial resolution is low. Psychophysical and computational studies show that chromatic contrast sensitivity is confined to a lower spatial frequency range than luminance contrast sensitivity (Kelly, 1983; Mullen, 1985; Derrico & Buchsbaum, 1991). These studies support the authors' hypothesis about interaction between color and blur, assuming that chromatic contrast (color differences) can facilitate recognition when high-frequency information is removed by a shape degrading factor as blur.

In one experiment of Wurm and his colleagues' study, both full-color and gray scale images were presented in two resolutions, blurred and unblurred, during a naming task. RTs were shorter in the full-color unblurred condition and longest in the gray scale blurred condition. They concluded that color does improve recognition of food objects whether measured as accuracy or RT, but they did not find the hypothesized interaction between color and spatial resolution. Two additional experiments were conducted to examine the origins of this effect. They investigated if shape prototypicality or color diagnosticity facilitated object recognition. They found that participants were faster at recognizing images judged to be highly prototypical (where the object is shown from its most common point of view), but that less prototypical images benefit more from color, that is, show a greater reduction in RT. These findings are consistent with Biederman and Ju (1988) view that primary access to object recognition uses structural (geometrical) representation of objects and this representation is in part generated by the presence of color. The results of Experiment 5 suggested that participants' explicit knowledge about food color (diagnosticity) does not account for the advantage of color in real-time object recognition.

The authors questioned how color and shape could act additively and non-interactively in object recognition. They argued that perhaps color contributes to an early stage of contour extraction and scene segmentation (De Valois and Switkes, 1983; Walls, 1942). That role is likely to rely on low spatial frequencies and hence, be relatively insensitive to blur. Thus, they concluded that although color does improve object recognition, the mechanism is probably sensory, rather than cognitive in origin. Otherwise, it would be related to people's knowledge of the colors of things, but this would not match with the results of their color-diagnosticity experiment (Wurm et al., 1993).

Several of these experiments concluded that shape is the basic element in object recognition (Ostergaard and Davidoff, 1985; Biederman and Ju, 1988; Wurm et al., 1993; Joseph and Proffitt, 1996) and that color plays a secondary role, facilitating object naming as a final step in object identification (Ostergaard and Davidoff, 1985; Wurm et al., 1993). But when object shape is degraded, color may play a more important role facilitating object recognition by scene segmentation (Biederman and Ju, 19880).

The discrepancy that exists among the researchers related to the role of color in object recognition, has originated a similar question about the use of color in multisensored fusion, in which artificially colored images are supposed to improve human performance in target detection and situational awareness. Part of the discrepancy of these latter studies may be originated by the different fusion algorithms used or by the wide variety of psychophysical tasks employed to measure behavior (Sinai et al., 1999b), as can be seen in the following summarized experiments.

Waxman, Gove, Seibert, et al. (1996) conducted an experiment trying to evaluate human perception during a visual search task. The detection of embedded small low-contrast targets in natural night scenes, was measured in terms of reaction time, and accuracy. Visible, infrared, color fused, and two forms of fused gray scale images, were shown to the participants, whose task was to determine whether the hidden target was on the right half or the left half of the screen. Although the report of this study does not show any statistics supporting the results, RTs during the detection task were fastest when color fused imagery was used, across various levels of target contrast.

Toet, Ijspeert, Waxman and Aguilar (1997) investigated if the increased amount of detail in the fused images can yield an improved observer performance in a task that requires situational awareness. Fused images were obtained from low visible and thermal signals, using two different fusion methodologies. The stimuli presented to the participants were in six different chromatic formats: Fused color images generated by two fusion algorithms, gray level images representing the luminance component of the fused color images, and gray level images representing the signals of the low-visible and the infrared cameras. The task required the detection and localization of a person in the displayed scene, relative to some characteristic details that provide the spatial context.

Visual and thermal contrasts were low, since stimuli were collected just before and after sunrise. Visual contrast was low due to low luminance of the sky. Thermal contrast was also low due to the similar temperature of the objects in the scene. The authors hypothesized that the fusion of images registered in these conditions would result in images that represented both the context (background) and the details with a large thermal contrast (like people) in a single composite image. The results showed that participants could indeed determine the location of a person in a scene with a significantly higher accuracy when they performed with fused images, compared to the other chromatic formats. The two color fusion algorithms yielded the best overall performance, producing error rates of 1.5% and 1.9%, while the corresponding gray scale fused images, respectively, produced error rates of 4.5% and 4.9%. The error rate for the thermal images was 8%, and for the visual images was 20%. The authors concluded that color contrast in fused imagery does help in target detection.

The objective of the study conducted by Steele and Perconti (1997) was to determine whether color fusion processes, were of benefit to helicopter pilots in the performance of night helicopter flights. Specifically, the authors investigated whether adding synthetic color to night vision multisensor (visible near infrared and long wave infrared) fused imagery, aided pilots in interpreting spatial relationships and improving situational awareness. The study consisted of a part task simulation, with three task groups: object recognition and identification, horizon perception and geometric perspective tasks. Object recognition and identification tasks are those tasks that required the participant to either determine if a specific object was present, locate a specific object and determine its position in the field of vision, and provide detail information about an object. Horizon perception tasks are those tasks that required the participant to determine whether or not the perceived horizon was level. Geometric perspective tasks required the participant to identify the shape or orientation of an object using monocular depth perception cues.

Images were presented in five different chromatic formats: I^2 monochrome, FLIR monochrome, a gray scale fusion algorithm and two different color fusion algorithms. Each task group yielded different results for the three general types of visual tasks used, although in general fusion based formats resulted in better participant performance. The authors concluded that the benefits of integrating synthetic color to fused imagery are dependent on the color algorithm used, the visual task performed, and scene content. In the object recognition task, both the FLIR and the gray scale fusion formats resulted in significantly faster RTs. In the horizon perception tasks no significant differences were found among response times and accuracy. In geometric perspective tasks the gray scale fusion algorithm produced significantly faster RTs than the FLIR alone. There were no significant differences among the other formats. The two color fusion algorithms examined in this study represent two very different approaches. Therefore, it is not surprising to find these two algorithms on opposing ends on some of the data plots of this study (Steele and Perconti, 1997).

The purpose of the study conducted by Krebs et al. (1998) was to modify the existing F/A-18 targeting FLIR system by adding a dual-band color sensor to improve target contrast and standoff ranges. The authors argued that objects viewed by low-light and infrared sensors would have dramatically different contrast levels between each system. Therefore, displaying these variations as color differences should improve target-background contrast and increase the dynamic range of the scene. When searching for a target, color should help by giving better context to the scene, as a result of the higher contrast among objects in the scene (scene segmentation), thus allowing for more efficient pilot orientation and target detection.

This experiment used eight nighttime video sequences collected from an early prototype fusion sensor system developed by Texas Instruments and the Night Vision and Electronic Sensors Directorate (NVESD). Each of the sequences was presented in five different image formats: low light visible imagery, infrared imagery, gray scale fused imagery and two different color fused imageries. It was hypothesized that these images should be maximally optimized for target discrimination. A standard visual search task was used to assess whether pilots' situational awareness was improved by using sensor-fused imagery. Participants responded faster to the infrared target compared to one of the color fused target, while the other color fused target showed no significant difference. These results generally agree with Steele and Perconti's (1997) study that used the same videotaped sequences. The authors concluded that color fusion did not improve pilots' situational awareness. Pilots reported that the color fused scene appeared unnatural due to the choice of colors. However, pilots did report that color fused objects were easier to discriminate than IR or I^2 objects, because of the color contrast that facilitates discrimination from the background noise. Therefore, color fusion may be more appropriate for targeting applications compared to navigation and pilotage applications.

The study conducted by Sinai, McCarley, Krebs and Essock (1999b) compared performance on two different tasks, an object recognition task and a situational awareness task. The authors hypothesized that performance on these two very different tasks would be differently affected both by the single sensor imagery and by the fused imagery. They hypothesized that performance on the detection/recognition task should be better for the IR imagery, because IR images usually have higher contrast than the I^2 image. Likewise, they hypothesized that performance should be slightly better for the I^2 imagery compared to the IR imagery for the situational awareness task, because IR imagery has lower resolution than the I^2 imagery. The authors also argued that the fused imagery would result in performance at least as good as the better of the two single band sensors.

Stimuli were images collected using long-wave IR sensor and I^2 low-light sensor. Six image formats were tested: single band IR and low-light formats, two color-fused formats and two achromatic fused formats, with each of the fused formats using IR imagery of white-hot polarity or black-hot polarity respectively. Two experiments were conducted. The first required participants to detect a target (person, vehicle or neither) against naturalistic backgrounds. The second measured participants' situational awareness by asking them to decide whether the scene was inverted or not.

Significant differences were found between the white-hot color fused error rates and the white-hot gray scale fused error rates for both tasks. Thus, the false-color of the fusion algorithm improved performance for this format and for both tasks. The only difference between the two formats was the addition of color. In the other fused format tested, however, color not only did not improve performance but even actually hindered performance by increasing error rates in both tasks. The results of this study showed great evidence for the benefits that color-fused imagery can produce in human performance, but also demonstrated how drastically results may vary according to tasks or algorithms used in the research (Sinai et al., 1999b).

In sum, several of these experiments concluded that color fusion facilitates target detection (Waxman et al., 1996) and situational awareness (Toet et al., 1997; Sinai et al., 1999b), one concluded that just targeting applications but not situational awareness may benefit from a color fusion scene (Krebs et al., 1998) while Steele & Perconti (1997) argued that the benefits color fusion depends on the color algorithm used, the visual task performed and scene content.

Summarizing the plausible benefits generated by the use of colored imagery, there is certain evidence that color may play an important role in object recognition when shape is degraded, both by means of scene segmentation in a bottom-up process, and by accessing stored knowledge in a top-down process, if colored imagery is congruent. For these same reasons, the use of color in fused imagery, where most of the times the contours of the objects will not be sharply defined, seems to be useful too in object recognition at least achieving a bottom-up process in which color contrast can facilitate contour definition, although there exists the possibility that color incongruency may originate disruptive effects, as it was shown in the reviewed literature. Therefore, it seems to be enough support to move forward in the research regarding the role of natural color and false color in object recognition.

F. HYPOTHESIS

In an effort to continue in this field of research, avoiding some of the deficiencies detected in the past and summarizing several of different techniques used in previous studies, this thesis will conduct a human performance experiment by measuring reaction times and error rates during a standard object naming task, trying to examine how natural and artificial color facilitates object recognition when objects' shape information is degraded. Naming was chosen as the psychophysical task for this experiment for two reasons. First, it provides a way to check the accurate and positive identification of the object presented in each stimulus to the participant. Also, because if color affects the processing of objects at any stage from early registration to the availability of the object name, this should be reflected in the object naming latencies (Ostergaard and Davidoff, 1985).

Digital photographs of natural objects (fruits and vegetables) were used. Common food objects also provide a favorable domain for studying the interaction of color and shape due to their natural although limited variation of both attributes within a category (Wurm et al., 1993). The familiarity and non-arbitrary colors of these objects might encourage participants to use color for recognition, perhaps especially in those cases when shape is no so helpful due to its similarity among several stimuli.

The effect of natural and artificial color was examined by comparing natural and false color imagery with their gray scale counterparts as a control for luminance. Since colored images and their gray scale equivalents were matched in luminance, any advantage measured in the colored imagery should have been originated by the presence of color.

Gaussian monochromatic noise was used as an image-degrading factor. The aim of using noise was to achieve some type of image degradation in order to examine how recognition might be affected under the degraded viewing conditions that occur with night vision devices.

It was hypothesized that if stored color knowledge affects object recognition, shorter RTs and smaller error rates would occur within the natural color images across all levels of noise, and that the difference in RTs and error rates between natural color and false color images would be largest in the conditions with the greatest amount of noise. Faster RTs and smaller error rates were expected within the natural color images because participants would be able to use color information to access stored knowledge of the participants would be able to use color information to access stored knowledge of the objects' chromatic features. Larger effects of natural color images were also expected in the conditions with higher levels of noise because here, since the objects' shape information was degraded, subjects might be encouraged to rely more heavily on color information to recognize the stimuli. The longest RTs and greatest error rates were expected within the gray scale images, because participants would not be able either to accomplish scene segmentation or to access stored knowledge during the object recognition task. Intermediate results would be achieved by false color images, because participants, although they were not able to access stored knowledge of color, at least they would be able to achieve scene segmentation and speed up recognition, compared to gray scale images. The four stated hypotheses are summarized below:

- Shorter RTs and smaller error rates were expected within natural color stimuli across all levels of noise.
- Differences in RTs and error rates between natural color and false color stimuli, were expected largest for greatest levels of noise.
- Longest RTs and greatest error rates were expected within the grayscale images.
- Intermediate results were expected for false color images.

These will be the Alternative Hypotheses for the statistical tests. The Null Hypotheses will be that there are no differences.

THIS PAGE INTENTIONALLY LEFT BLANK

III. EXPERIMENT

A. METHODS

1. Participants

Thirteen students (eleven male and two female) from various military services and job specialties, undergoing academic studies at the Naval Postgraduate School, and ranging in age from 28 to 38, voluntarily participated. Participants who volunteered for this study might not represent a broad spectrum of the population but their psychophysical characteristics were very similar to those of potential NVDs operators. All participants were screened for normal color vision with the Pseudo-isochromatic Plates and had at least 20/20 corrected vision. Participants were naïve to the purpose of the experiment. All participants were native English speakers. All participants granted informed consent prior to participation.

2. Apparatus

The experimental workstation consisted of a 200 MHz Pentium personal computer equipped with a Texas Instrument TMS-340 Video Board and the corresponding TIGA Interface to Vision Research Graphics software. The stimuli were

MF-8521 High Resolution color monitor (21" X 20" viewable area) equipped with an anti-reflect, non-glare, P-22 short persistence CRT. Pixel size was .26" horizontal and .28" vertical. Resolution was 800 X 600 square pixels and the frame rate was 98.7 Hz. Luminance of the monitor was linearized by means of an eight-bit color look-up table (LUT) for the red, blue and green guns. Moderate ambient luminance was maintained during the test. Viewing distance was approximately 100 cm and the participants were free to move their heads.

3. Stimuli

Experimental stimuli were digital images of twenty-three fruits and vegetables whose names appear in Table 1. Images were photographed by the experimenter with a Kodak digital camera, Model DC50. Objects were photographed in the early afternoon under natural daylight against a background of white paper. Each object was photographed from four different viewpoints, all of them judged to be canonical by the experimenter. Viewing distance was varied in order to make all objects occupy approximately the same area within the photograph. From the initial set of twenty-three objects photographed, the nineteen objects judged by the experimenter to be the most common and easy to name were selected for use in the experimental trials. The four remaining objects were reserved for use in the practice trials.

Images were then manipulated using commercially available image processing software (Adobe Photoshop 4.0). Images were first cropped to a rectangle 600 X 500

STIMULUS OBJECTS		
APPLE	AVOCADO(*)	BANANA
BEANS	BROCOLI	CABBAGE
CARROT	COCONUT	CORN
CUCUMBER	GARLIC(*)	GRAPES
LEMON	MUSHROOM	ONION
ORANGE(*)	PEAS	PEAR
PEPPER	POTATO	RADISH
TOMATO	ZUCCHINI(*)	
(*) Object used for practice trials only.		

Table 1: Object names.

pixel size, subtending 11.4° X 10.2° of visual angle from a viewing distance of 100 cm, and then rendered in each of four different color formats: natural hue chromatic, natural hue achromatic, false hue chromatic and false hue achromatic. False hue images were obtained by replacing the color of each pixel in a natural hue image with its complementary color. Complementary colors are a pair of colors which when mixed additively, appear as white. Along a color wheel, complements are any two colors separated by 180 degrees, that is, any two colors at opposite ends of a single diameter. For consistency, all images of natural hue were reassigned a value of +180 degrees in order to get their false color counterparts. The value of +180 degrees was chosen arbitrarily and is of no theoretical significance. Natural hue achromatic and false hue achromatic images chromatic natural hue and false hue images, respectively, to gray scale. Gray scale images matched their chromatic counterparts in pixel-by-pixel luminance. The purpose of these gray scale images was to provide a control for any changes in luminance that accompanied manipulations of color within chromatic images.

Once the four sets of stimuli were obtained, degraded images were produced by addition of achromatic gaussian noise to undegraded images. Noise was added by increasing or decreasing the intensity of each pixel within an image by a value draw pseudo-randomly from a Gaussian distribution with a mean of 0. The standard deviation (SD) of this distribution determined the level of degradation. Three levels of noise were used. At the first level images were not degraded (SD of noise distribution = 0). At the second and third levels, images were degraded with values drawn from Gaussian distributions with SDs of 50 and 100 units respectively. Color formats and degradation levels were crossed factorially.

Mean luminance of each image in the experimental set of stimuli was calculated. The mean value and standard deviation of the luminance values for each color format and level of noise was computed. These results are shown in Table 2. As it is shown in Table 2, average luminance for all color formats is almost a constant for each level of noise, although values of individual images changed more drastically. Pixel values of less than zero or greater than 255 were set to values of zero and 255, respectively, when noise was added. Therefore, mean pixel values decreased slightly as noise increases, tending toward a value of 128 (50 cd/m2). The mean luminance for each chromatic format is almost constant too, (Natural hue chromatic = 58.15 cd/m^2, false hue chromatic = 57.92 cd/m^2, cd/m^2, natural hue monochromatic = 58.08 cd/m^2, false hue monochromatic = 58.12 cd/m^2). Therefore, differences in RTs between color images and their gray scale counterparts cannot be attributed to differences in luminance.

		COLOR FORMAT			
		Natural Hue Chromatic	False Hue Chromatic	Natural Hue Monochromatic	False Hue Monochromatic
NOISE LEVEL	0	58.84	58.61	58.85	58.83
		9.31	8.63	9.20	8.43
	1	58.69	58.45	58.60	58.63
		8.88	8.82	8.81	8.07
	2	56.89	56.70	56.79	56.89
		7.08	6.56	7.13	6.35

Table 2: Mean values and standard deviations of luminance for each color format and level of noise in cd/m^2.

4. Procedure

Each of nineteen objects was presented at random in twelve different formats, and from two different points of view selected at random from among the four available views of each object. A total of 456 (19 X 12 X 2) stimuli were presented to each participant as experimental trials, and fifteen stimuli were presented for practice purposes.

Each subject was thoroughly briefed on the background and procedures of the experiment and was given the opportunity to ask questions. Prior to testing, participants read a list of the nineteen food categories in the experimental trials and the four categories in the practice trials. They were told that their task was to name as rapidly and accurately as possible the object presented in each stimulus. They were also told that the objects would fill the viewing window on the screen (i.e., there would be no scale information) and that items could appear alone, or in groups of items of the same type (beans, grapes, peas and radishes).

Participants were tested one at a time. They were seated in front of the monitor at distance of 100 cm. The experimenter was seated in front of a different monitor in the same room, from which he could not see the stimulus images and remained unaware of the format in which each image was presented. There was a warning tone to alert the observer that the trial was going to start followed by a pause of 500 msec before the image was presented on the screen. Each image remained on the screen until the observer responded. Upon hearing the observer's response, the experimenter immediately pressed a key to stop the timer and one more key to record the accuracy of the response (1 for "true", 2 for "false"), based on the correct response that appeared on the experimenter's monitor. No feedback was provided following any response. The subsequent trial followed after an intertrial interval (ITI) of approximately 1,000 msec. A uniform gray patch of the same size as the food images was shown on the screen during ITI's. The experimenter allowed participants to relax for a short period of time after each group of 40 images. Each participant completed two experimental sessions, with each session composing a block of 228 trials. Within a block, participants observed each of the nineteen objects, once in each of the twelve image formats (19 X 12). The point of view, from which each object was viewed, was chosen randomly. The entire experiment lasted approximately 50 minutes (25 minutes for each session).

Each subject was given a block of 15 practice trials prior to the first session of the experiment. All the participants held both sessions on the same day. The practice trials were presented in the same format as the experiment stimuli. Upon completion, participants were offered a brief pause to ask any question. The actual experiment then started. Reaction time and accuracy were recorded for each trial.

5. Experimental Design

The experimental design for this study was a 2 X 2 X 3 X 2 within-subjects factorial design. Factors included color (chromatic or achromatic), hue (natural or false), level of noise (0,50,100), and block (Sessions 1 or 2). Sex was not considered as a factor for this experiment. Each of the 12 cells contained 38 observations per participant (19 objects X 2 replications) for a total of 456 data points per participant. Reaction times for incorrect responses, and all data from the 15 practice trials were excluded from data analysis. Previous calculations determined that the number of participants (13) was sufficient in order to achieve statistical power greater than 0.8 under all hypotheses.

B. DEVELOPMENT OF THE STATISTICAL MODEL

As with any psychophysical experiment, inconsistencies occur between various participants' RTs and error rates under different experimental conditions. These differences arise in part due to variances in individual participants, image conditions and manipulation. To account for these differences, the following model is proposed:

RT_{ijklmn} (or Error rates) = $Part_i + Color_j + Hue_k + Noise_l + Block_m + error_n$

Where $Part_i$ represents the ith participant of the experiment;

$Color_j$ represents the color of the image (chromatic or achromatic);

Hue_k represents the hue condition of the image (natural or false);

$Noise_l$ represents the level of achromatic Gaussian noise (0,50,100):

$Block_m$ represents each of the two sessions of the experiment (S1 or S2);

$error_m$ represents unaccounted variations within the model.

C. RESULTS AND DISCUSSION

Mean RTs and error rates for all twelve combinations of color conditions and levels of noise, averaged across participants, are shown in Table 3 and Table 4. These same results are also represented graphically in Fig. 11 and Fig. 12.

Figure 11 illustrates how RTs increased for all four color formats when noise increased. Natural color (NC) RTs were the shortest at each level of noise compared to

		COLOR CONDITION			
		Natural hue Chromatic	Natural hue achromatic	False hue chromatic	False hue achromatic
NOISE LEVEL	0	910.10	914.58	968.15	951.09
		11.09	9.76	12.92	15.11
	1	940.12	971.01	975.93	1005.88
		13.71	12.95	13.86	16.54
	2	1015.23	1091.01	1064.08	1146.12
		17.26	17.21	18.31	23.73

Table 3: Mean reaction times and standard errors (msec) for each level of noise and color condition.

		COLOR CONDITION			
		Natural hue Chromatic	Natural hue achromatic	False hue chromatic	False hue Achromatic
NOISE LEVEL	0	0.40	1.21	0.61	2.23
		0.28	0.44	0.34	0.66
	1	1.62	3.04	3.24	4.05
		0.57	0.78	0.72	0.84
	2	3.04	8.12	8.30	10.53
		0.88	1.37	1.28	1.49

Table 4: Mean error rates and standard errors (%) for each level of noise and color condition.

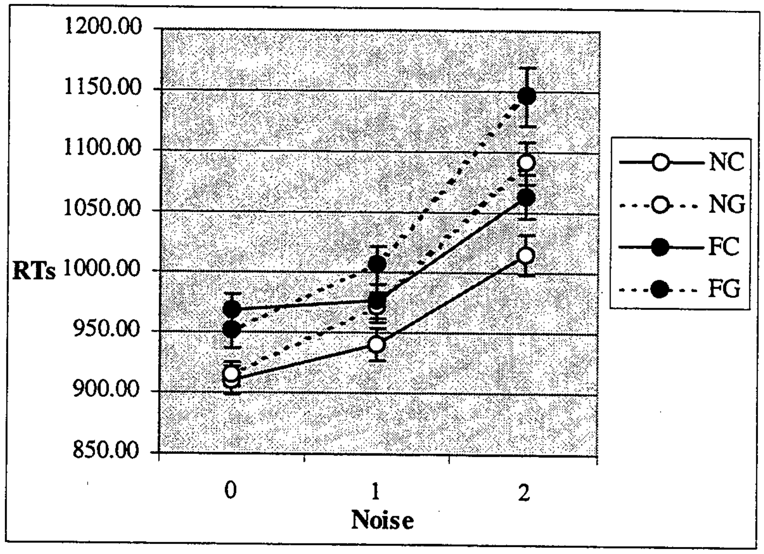

Figure 11: Mean reaction times (msec) for each level of noise and color condition, with one SEM error bars.

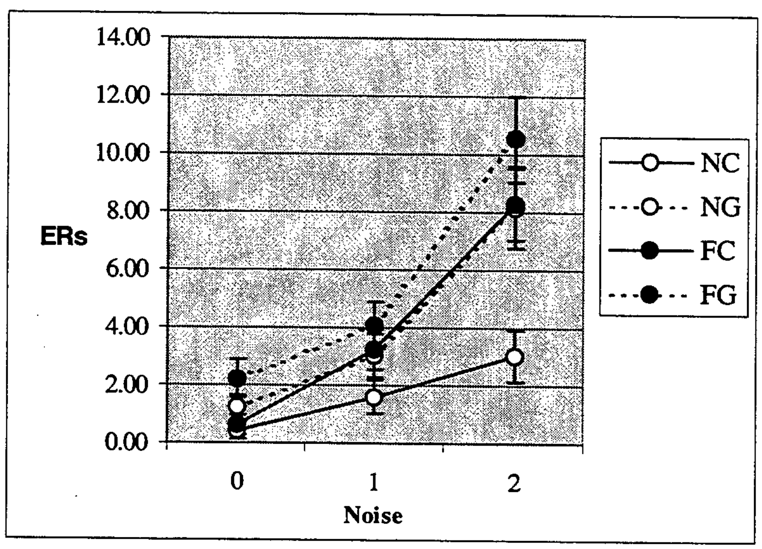

Figure 12: Mean error rates (%) for each level of noise and color condition, with one SEM error bars.

the other color formats, as was predicted by the first hypothesis. The differences in RTs between NC and FC conditions, however, did not increase as the level of noise increased, in opposition to the statement that was made in the second hypothesis. These differences were almost constant across all levels of noise, although RTs for NC images were always shorter than FC RTs at the same level of noise.

At level of noise 0, RTs were shortest for natural hue formats (NC and NG), and longest for artificial hue conditions (FC and FG). As the levels of noise increased, RTs for the achromatic conditions (NG and FG), became slower compared to the chromatic conditions (NC and FC). The difference in RTs between chromatic and achromatic stimuli increased as noise increased, reaching the longest RTs at the highest level of noise as it was stated in the third hypothesis. Also, although FC condition had the longest RT at level of noise 0, as noise increased its performance improved and it showed the second best result at level of noise 2, as it was stated in the fourth hypothesis.

There was a great similarity between RTs and error rates results. Figure 12 illustrates how NC error rates were smaller for each level of noise compared to the other color formats, as it was stated in the first hypothesis. At level of noise 0, error rates were very similar for NC and NG formats. FC error rates were almost the same as NC error rates, although for levels of noise 1 and 2, FC error rates were more similar to the achromatic formats (NG and FG), and its differences with NC stimuli increased as the level of noise increased, as was predicted by the second hypothesis.

Both figures show larger RTs and error rates for the achromatic conditions and intermediate results for the FC conditions in each level of noise, as was predicted by the third and fourth hypotheses.

Using the same results of the experiment, this study conducted the measurement of the advantage of using natural color versus false color, for different levels of noise. Because changes of hue also entailed changes of luminance within stimulus images, a direct comparison of RTs to NC and FC images cannot indicate effects of natural chromatic information. In order to assess the benefit of the use of color, therefore, Tables 5 and 6 express the differences in RTs and ERs, between achromatic and chromatic natural conditions (NG-NC) and between achromatic and chromatic artificial conditions (FG-FC) at each level of noise. These values will be referred to as natural color benefit and false color benefit. If there was any benefit originated by the use of color, chromatic conditions should have obtained better results than their gray scale counterparts and this advantage should have increased with increasing levels of noise. Were the benefits of color rendering the exclusive result of facilitated image segmentation, furthermore, then effects of natural and false color should have been similar across all levels of noise. Conversely, was natural color useful in accessing the stored information necessary for naming stimulus items, natural color benefit should have exceeded the benefits of false color, particularly at high levels of image noise where information about the stimulus items' shapes was most severely degraded. Also, these differences are shown in Fig. 13 and Fig. 14.

Figure 13 shows almost no advantage at level of noise 1 for natural conditions and a small, although non-significant, disadvantage for artificial conditions. As noise increases, color benefits increase too, with the largest advantage for the largest level of noise and very similar advantages both for natural and for artificial conditions. The use of either natural or artificial color seems to be similarly helpful regarding RTs in a recognition task, although NC RTs are always faster than their FC counterparts.

	Natural	Artificial
Level 0	4.48	-17.06
Level 1	30.89	29.95
Level 2	75.78	82.04

Table 5: Mean reaction time differences (msec) for each level of noise and hue.

	Natural	Artificial
Level 0	0.81	1.62
Level 1	1.42	0.81
Level 2	5.08	2.23

Table 6: Mean error rate differences (%) for each level of noise and hue.

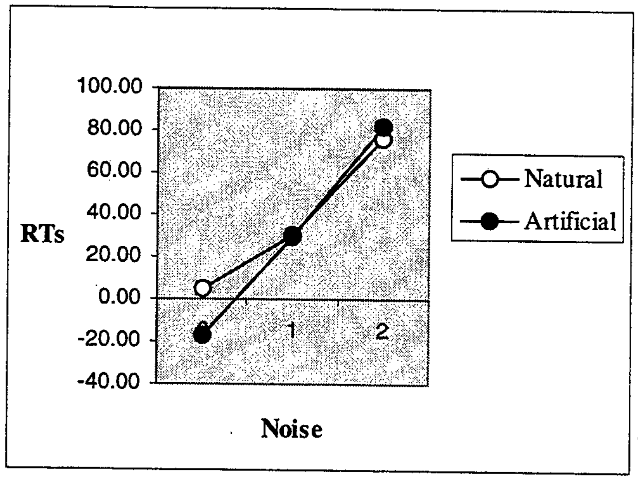

Figure 13: Mean reaction times color advantage (msec) for each level of noise and hue.

Figure 14 illustrates how for natural conditions, color benefit for error rates increased with the level of noise, but artificial conditions did not show a similar increase of benefit in error rates when the level of noise increased, although these differences were

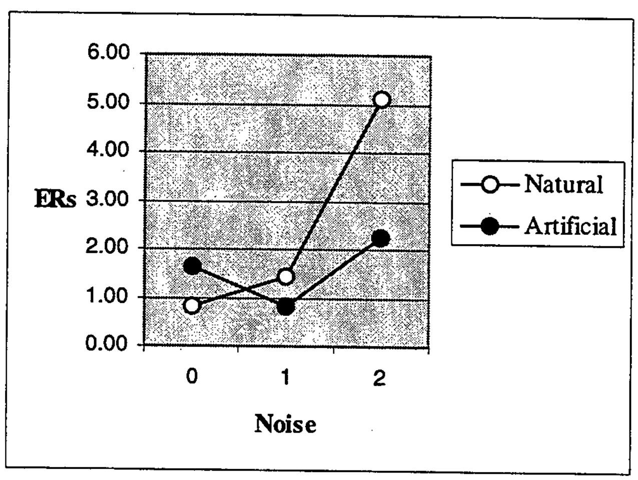

Figure 14: Mean error rates color advantage (%) for each level of noise and hue.

non-significant. Nevertheless, there always existed certain benefit in accuracy for each level of noise and each color condition.

To determine the appropriate statistical method to be used in the analysis of the results of this experiment, normality tests were conducted, using histograms and normal QQ-plot of residuals as diagnostic plots. These tests showed that the data failed to follow the properties of normality. In order to satisfy the assumption of normality, power transformations were applied to the RT and error rates data. RTs on trials on which participants responded incorrectly were treated as missing values. Repeated measures analyses of variance (ANOVAs) were performed on the transformed data, both for RTs and for error rates with a significance level of 0.01. Although the analyses were performed on 1/RT and squared root of ER, the terms RT and error rates are used for convenience throughout this study. Mean RTs in milliseconds (msec) and mean error rates in percent for each of the participants were calculated from individual performances for each condition. When RT and error rates means are reported in the text, these are untransformed data.

The analysis, with participants as a random variable, was a 2X2X3X2 repeated measures ANOVA, with the independent variables Hue (natural, false), Color (chromatic, achromatic), Noise (0, 50, 100), and Block (1,2). The first three independent variables were repeated within subjects. The same ANOVA that was used for RTs was also used for error rates analysis.

The a priori hypotheses and some interesting interactions can be explored using univariate analysis on RT and error rates separately. ANOVA on the dependent variable

RT, showed significant main effects for: Color: $\underline{F}(1,5674) = 20.7366$, $\underline{p} < 0.01$; Hue: $\underline{F}(1,5674) = 36.0931$, $\underline{p} < 0.01$; and Noise: $\underline{F}(2,5674) = 141.0512$, $\underline{p} < 0.01$. Participants responded significantly faster when images were chromatic rather than achromatic, when hue was natural rather than artificial and when images were less degraded by Gaussian noise. Mean RT for chromatic images was 978.94 msec (Std. Dev. 122.4 msec) and for achromatic images was 1013.28 msec (Std. Dev. 131.1 msec). Mean RT for natural images was 973.68 msec (Std dev 120.6 msec) and for artificial images was 1018.54 msec (Std. Dev. 131.1 msec). Mean RTs for the three different levels of noise were: Level 0: 935.98 msec (Std. Dev. 105.4 msec), Level 1: 973.24 msec (Std. Dev. 106.4 msec), and Level 2: 1079.11 msec (Std. Dev. 124.8 msec). The ANOVA results and the above values clearly support a significant difference in mean RTs across color, hue and noise conditions.

Similar results were obtained for the dependent variable ER. ANOVA showed also significant main effects for: Color: $\underline{F}(1,285) = 17.5616$, $\underline{p} < 0.01$; Hue: $\underline{F}(1,285) = 16.9579$, $\underline{p} < 0.01$; and Noise: $\underline{F}(2,285) = 54.6472$, $\underline{p} < 0.01$. Mean error rates for chromatic images was 2.87 (Std. Dev. 3.58) and for monochromatic images was 4.86 (Std. Dev. 4.89). Mean error rates for natural images was 2.91 (Std dev 3.76) and for artificial images was 4.82 (Std. Dev. 4.77). Mean error rates for the three different levels of noise were: Level 0: 1.11 (Std. Dev. 1.76), Level 1: 2.99 (Std. Dev. 2.71), and Level 2: 7.50 (Std. Dev. 5.11). The ANOVA results and the above values clearly support a significant difference in mean error rates across color, hue and noise conditions. Participants were not only faster but also more accurate when chromatic, natural and non-degraded images were shown to them.

Once the significance of the main effects was tested, the factorial interactions were analyzed. The next set of figures was constructed to assist in analyzing factorial interactions for both dependent variables. Figure 15 and Figure16 illustrate the Hue by Color interaction. The lines joining mean RTs and error rates for the same Color level are roughly parallel across the two levels of Hue. Apparently, there is no interaction between these two factors at the 1% significance level. ANOVA yields these results: Dependent variable RT $\underline{F}(1,5674) = 4.5517$, $\underline{p} = 0.0329$; dependent variable ER: $\underline{F}(1,285) = 1.1320$, $\underline{p} = 0.2882$, confirming the assumption derived from the graph inspection.

The non-significance of this interaction for both dependent variables shows that although participants were faster and more accurate with chromatic images compared to their achromatic counterparts, these differences in RTs and error rates were similar for both natural and false hue. It seems that the advantage of NC images over NG images (derived from the presence of color) is similar to the advantage of FC over FG images. These results suggest that false color is not interfering with recognition; otherwise the difference between natural conditions (NG –NC) compared to the difference between artificial conditions (FG-FC) should have been significant.

Figure 17 and Figure 18 illustrate the Noise by Color interaction. Figure 17 shows how as the level of noise increases, the differences in RTs for each level of noise increase too, with faster RTs and greater accuracy for the chromatic images. Apparently there is interaction between these two factors for the dependent variable RT. ANOVA yields these results: Dependent variable RT $\underline{F}(2,5674) = 9.4622$, $\underline{p} < 0.01$; dependent variable ER: $\underline{F}(2,285) = 1.4343$, $\underline{p} = 0.2399$, therefore just the interaction for RT is significant.

yields these results: Dependent variable RT $F(2,5674) = 9.4622$, $p < 0.01$; dependent variable ER: $F(2,285) = 1.4343$, $p = 0.2399$, therefore just the interaction for RT is significant.

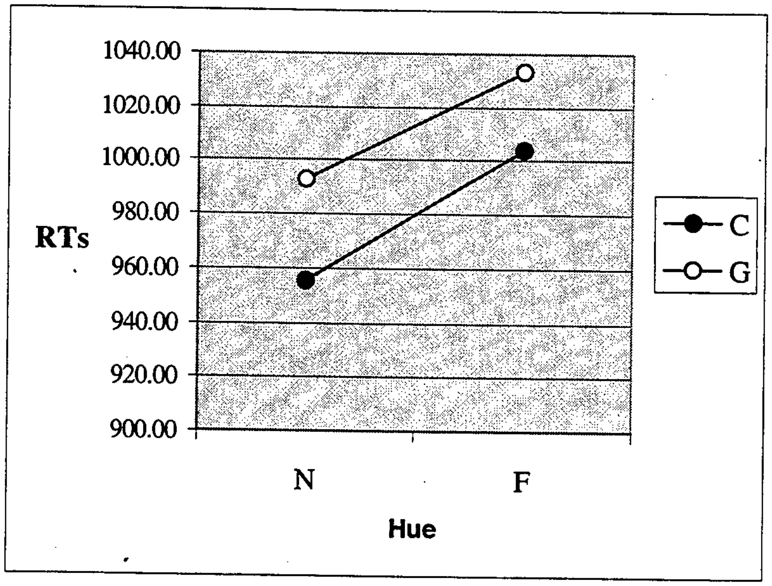

Figure 15: Mean reaction times (msec) for hue and color conditions.

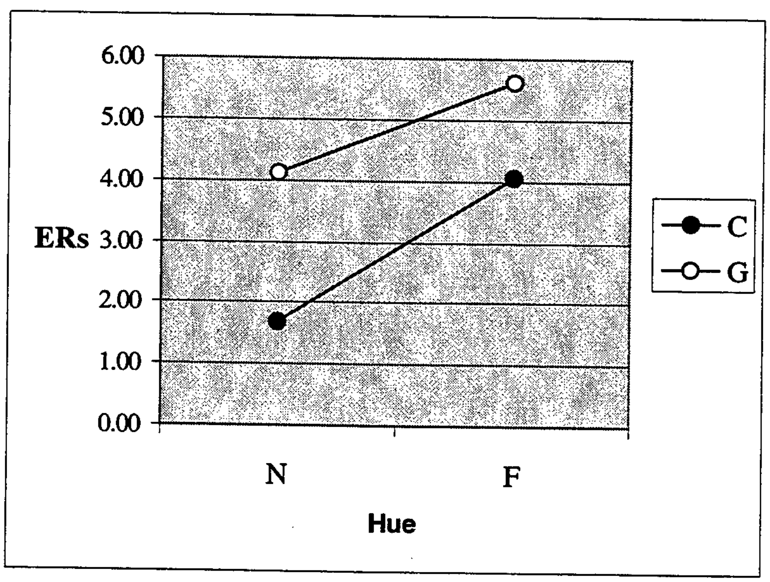

Figure 16: Mean error rates (%) for hue and color conditions.

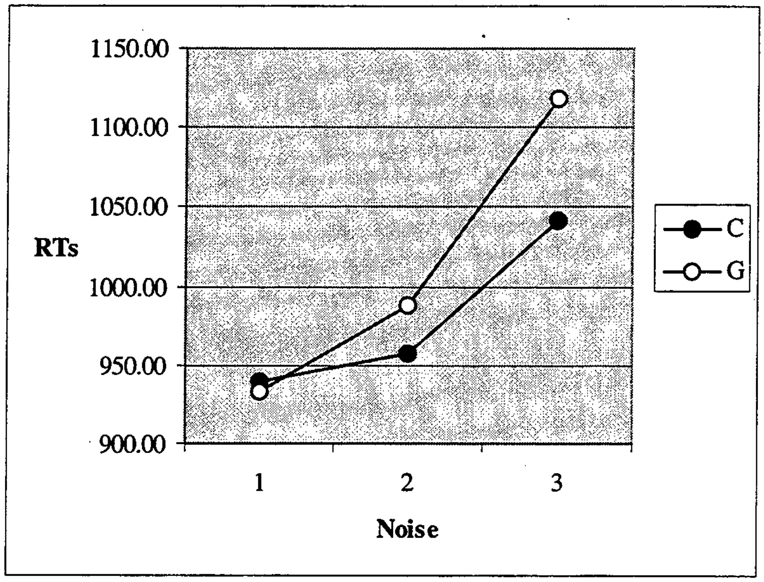

Figure 17: Mean reaction times (msec) for noise and color conditions.

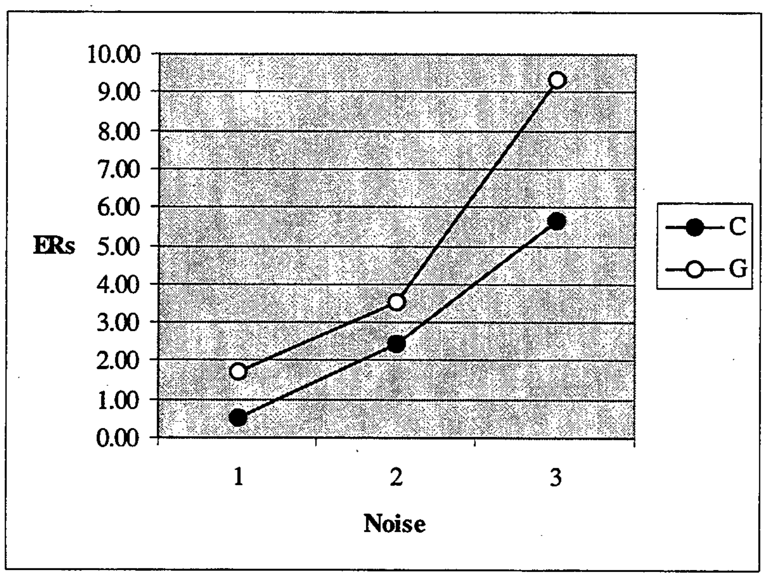

Figure 18: Mean error rates (%) for noise and color conditions.

The significance of this interaction for the dependent variable RT shows that participants were not only faster with chromatic images compared to their achromatic counterparts but also that the difference between chromatic and achromatic stimuli increased as the levels of noise increased. These results suggest that color is playing a role in object recognition speeding the identification of the stimuli when their shape is degraded and that the more degraded the objects are, the more helpful color is. As noted above, the absence of an interaction between level of hue (natural or false) and level of color (chromatic or achromatic) indicates that this effect is the result of facilitated image segmentation.

Figure 19 and Figure 20 illustrate the Noise by Hue interaction. Figure 19 shows how the lines that represent mean RTs both for natural and false images across the three levels of noise, remain parallel to each other. Apparently there is no interaction between these two factors for the variable RT.Figure 20 shows how these lines slightly diverge for increasing levels of noise, indicating a possible interaction between these two factors for the dependent variable ER. ANOVA yields these results: Dependent variable RT $\underline{F}(2,5674) = 0.3262$, $\underline{p} = 0.7217$; dependent variable ER: $\underline{F}(2,285) = 2.7447$, $\underline{p} = 0.0659$, indicating no significance of the hue by noise interaction for any of the dependent variables RT or ER. The non-significance of this interaction for both dependent variables RT and error rates shows that although participants were faster and more accurate with natural hue images than with their artificial counterparts, the difference between these two formats did not increase with increasing levels of noise. These results suggest that false color is not interfering with recognition as the level of noise increases, in a similar way as it was shown for the Hue and Color interaction.

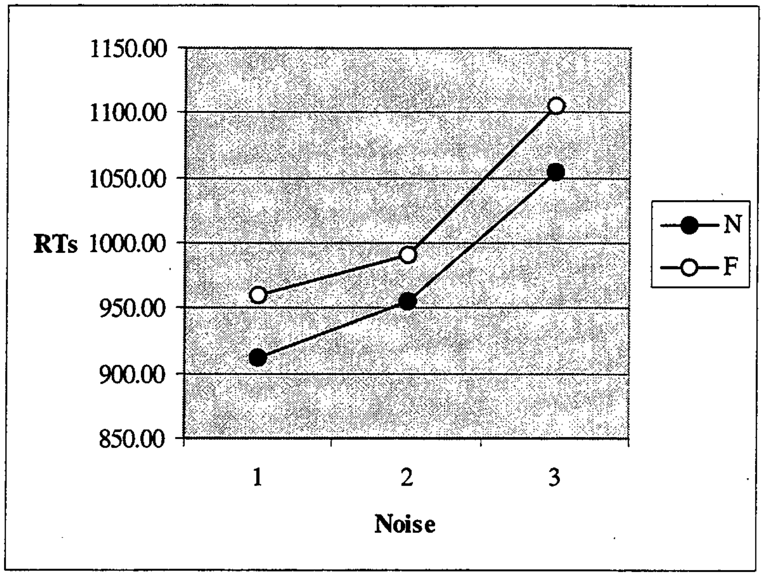

Figure 19: Mean reaction times (msec) for noise and hue conditions.

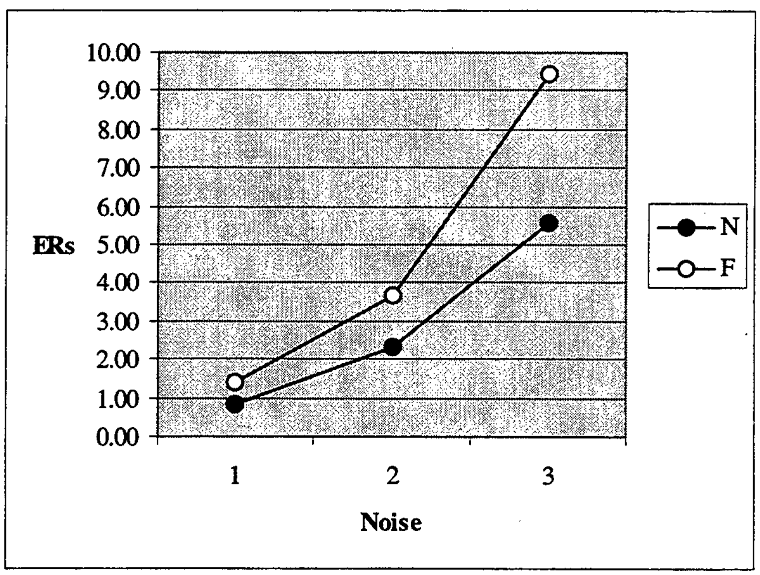

Figure 20: Mean error rates (%) for noise and hue conditions

Factorial three-way interaction for both dependent measures resulted non-significant according to ANOVA results: dependent variable RT: $F(2,5674) = 0.1944$, $p = 0.8233$; dependent variable ER: $F(2,285) = 1.2618$, $p = 0.2847$. Based on these results, the second a priori null hypothesis (no interaction of NC and FC conditions) cannot be rejected. The non-significance of this interaction shows that the difference between natural hue images and their gray scale counterparts (NG-NC) and between false hue images and their respective achromatic counterparts (FG-FC) does not change significantly when the levels of noise change. These results suggest that both the beneficial effects of natural color and false color remain similar for increasing levels of noise.

Experiment data analysis showed that RTs for color stimuli were faster compared to gray scale images and that this effect increased when the level of noise increased. These results suggest that both natural color and false color conditions might be beneficial in object recognition. The advantage of using natural color seems to be similar to the advantage that is obtained when artificial color is used. Therefore false color does not seem to be disruptive in recognition tasks. Both natural and false color stimuli are similarly helpful at different levels of noise, such that even for high degradation levels false color remains non-disruptive in object recognition. All these results also suggest that participants are not using color to recognize the objects in a top-down process. They are just fulfilling a bottom-up process using color for image segmentation, without any effect of the level of color (natural or false) or of the level of noise. If they were using stored knowledge of color to recognize objects, the advantage of using natural color should be larger than the advantage obtained from the use of false color, and this is not the case.

It should be recalled that FC images were obtained by means of hue manipulation of the original NC images. The significant difference of performance by the participants at level of noise 0, when dealing with these images, could have been originated by two kinds of reasons: i) false color is disruptive in object naming tasks, based on incongruency with the stored knowledge of color; ii) changes in luminance with respect to the NC images, originated during hue manipulation. All achromatic stimuli, both with natural or false hue, were obtained from their chromatic counterparts without introducing any change in luminance during the transformation. Luminance of NC stimuli is the same as the luminance of NG stimuli. For the same reason, luminance of FC stimuli is the same as the luminance of the FG stimuli. Therefore, differences in responses between NG and NC stimuli or between FG and FC stimuli, are due just to changes in color. Also, ANOVA results for hue, color and noise effects showed that false color was not disruptive during the naming task conducted in this experiment. Thus, differences in responses between NC and FC images are due just to changes in luminance.

NG images achieve better performances than their FG counterparts for all different levels of noise and for dependent variable RT. The results of these two chromatic conditions were expected to be similar. In this case, these different results cannot be explained based on differences in color, given that both conditions are achromatic. These diverging results should have been originated then by changes in luminance, possibly introduced when hue was manipulated, based on the similar value of the differences with their chromatic counterparts (NG-NC vs. FG-FC), both for RTs and error rates, and based also on the fact that gray scale images were obtained from manipulation of their respective chromatic counterparts, just eliminating color. Therefore, differences between NC and FC stimuli for RTs are due just to changes in luminance.

There is a possibility that could explain how these manipulations in hue could affect the luminance of the image. Measures of luminance for NC and FC stimuli showed that luminance for some images increased and for others decreased when the change of hue was conducted. Although the mean luminance of all the images for each format did not change (at level of noise 0 mean luminance for NC images was 150.06; Sdev 14.86 and for FC was 149.46; Sdev 13.79), changes in luminance could have affected each image in a different way, with luminance increasing in some places of the image and decreasing in others. This could have left mean luminance for each whole image unchanged but would have changed the contrast within the images. Poorer contrast in the vicinity of the object's contour could have made object recognition more difficult to achieve.

Paired comparisons using Tukey's method were conducted at each level of noise, and for both dependent variables RT and error rates, among the different color conditions. These results are represented graphically in Table 7. Underlined pairs are non-significant. The numeric results of these comparisons can be seen in Tables 8 and 9. These tables show how, at each level of noise, participants were faster and more accurate with NC stimuli than with any other condition.

Based on these results the first null hypothesis can be rejected. Differences in RTs between NC and FC stimuli resulted significant at level of noise 0 but there were non-significant at other levels of noise and the difference between them did not increase as the levels of noise increased so, the second null hypothesis cannot be rejected. The third and fourth null hypotheses can be rejected based on the facts that gray scale images achieved the longest RTs and greatest error rates at each level of noise, and the FC images achieved intermediate results, as it was hypothesized. For the dependent variable error rates, just NC stimuli resulted significantly different from FG stimuli at level of noise 0, and level of noise 2.

RTs Paired Comparisons

Noise Level 0	NC	NG	FG	FC
Noise Level 1	NC	NG	FC	FG
Noise Level 2	NC	FC	NG	FG

ERs Paired Comparisons

Noise Level 0	NC	FC	NG	FG
Noise Level 1	NC	NG	FC	FG
Noise Level 2	NC	NG	FC	FG

Table 7: Tukey's Method Paired Comparisons.

Noise level 0	FC	FG	NG	NC
FC	X	0.000019	0.000061 (SIG)	0.000066 (SIG)
FG	0.000019	X	0.000042 (SIG)	0.000047 (SIG)
NG	0.000061 (SIG)	0.000042 (SIG)	X	0.000005
NC	0.000066 (SIG)	0.000047 (SIG)	0.000005	X
W=0.000041				
Noise level 1	**FG**	**FC**	**NG**	**NC**
FG	X	0.000031	0.000036	0.000070 (SIG)
FC	0.000031	X	0.000005	0.000039
NG	0.000036	0.000005	X	0.000034
NC	0.000070 (SIG)	0.000039	0.000034	X
W=0.000043				
Noise level 2	**FG**	**NG**	**FC**	**NC**
FG	X	0.000044	0.000067 (SIG)	0.000112 (SIG)
NG	0.000044	X	0.000023	0.000068 (SIG)
FC	0.000067 (SIG)	0.000023	X	0.000045
NC	0.000112 (SIG)	0.000068 (SIG)	0.000045	X
W=0.000048				

Table 8: Mean reaction times paired comparisons for each level of noise and color format (Transformed data).

Noise level 0	FG	NG	FC	NC
FG	X	0.390	0.713	0.856 (SIG)
NG	0.390	X	0.323	0.466
FC	0.713	0.323	X	0.143
NC	0.856 (SIG)	0.466	0.143	X
W=0.829				
Noise level 1	**FG**	**FC**	**NG**	**NC**
FG	X	0.212	0.269	0.739
FC	0.212	X	0.057	0.527
NG	0.269	0.057	X	0.470
NC	0.739	0.527	0.470	X
W=1.134				
Noise level 2	**FG**	**FC**	**NG**	**NC**
FG	X	0.363	0.394	1.501 (SIG)
FC	0.363	X	0.031	1.138
NG	0.394	0.031	X	1.107
NC	1.501 (SIG)	1.138	1.107	X
W=1.290				

Table 9: Mean error rates paired comparisons for each level of noise and color format (Transformed data).

In order to investigate a possible learning effect caused by the use of the first session of the experiment as training for the second one, the independent variable Block was included in the model, with two levels, Sessions 1 and 2, looking for a significant difference between the results of both sessions. A greater learning effect for the FC conditions could have obscured the assumed detrimental effects of FC in object recognition by decreasing RTs and error rates during the second session. This effect could be based on the knowledge achieved by the participants during the first session of the experiment. Main effect of Block and interactions with Hue and Color were therefore analyzed for both RTs and error rates. ANOVA yielded these results: significant main effect for Block, on the dependent variable RT: $F(1,5674) = 67.9391$, $p < 0.01$; and on the dependent variable ER: $F(1,285) = 15.3184$, $p < 0.01$. None of the interactions were significant for any of the dependent variables. These were the results for the interactions: Hue by Block interaction for RT: $F(1,5674) = 0.6212$, $p = 0.4306$; for error rate $F(1,285) = 0.00263$, $p = 0.9591$. Color by Block interaction for RT: $F(1,5674) = 0.0653$, $p = 0.7983$; for error rate $F(1,285) = 0.5874$, $p = 0.4441$. These results suggest that participant responses were faster and more accurate during the second session, possibly caused by a learning effect during the first session of the experiment. But they were not significantly faster at any specific color condition, therefore a greater learning effect, not just for FC but for any other particular color condition, could not be proven. Learning effect was similar for every color condition.

THIS PAGE INTENTIONALLY LEFT BLANK

IV. CONCLUSIONS

This experiment examined the role of natural and false color in an object recognition task, with degraded and non-degraded images, focusing on improving night vision devices that employ the new technology of color fusion displays.

Four hypotheses were stated in the introduction that summarized several assumptions based on previous research about the role of color in object recognition. The experimental design was employed to explore dependent measures as reaction time and accuracy in object recognition, critical factors when accomplishing military missions in which night vision devices are involved.

The results and discussion presented in the previous chapter supported rejecting all but the second null hypothesis. First, third and fourth null hypotheses were rejected, based on data analysis that showed how natural color images achieved the best performance at every level of image degradation; achromatic images achieved longest RTs and largest error rates, and false color stimuli reached an intermediate level of performance between these two groups of stimuli. There was a failure to reject that differences in RTs between natural color images and their false color counterparts increased for increasing levels of image degradation. These results are summarized in Table 10.

Data analysis suggest that differences in performance between natural and false hue stimuli were due to differences in luminance and not to chromatic differences in such

Null Hypothesis	Result	Conclusion
No differences in RTs or ERs between natural color stimuli and other color formats, across all levels of noise	Reject Null Hypothesis	Shorter RTs and smaller ERs within natural color stimuli across all levels of noise
No increasing differences in RTs or ERs between natural color and false color stimuli for increasing levels of noise	NOT reject Null Hypothesis	(Null hypothesis)
No differences in RTs or ERs between chromatic and achromatic stimuli across all levels of noise	Reject Null Hypothesis	Longest RTs and greatest ERs within the achromatic stimuli across all levels of noise
No differences in RTs or ERs between natural hue and false hue stimuli across all levels of noise.	Reject Null Hypothesis	Intermediate results for false hue stimuli across all levels of noise.

Table 10: Summary of the results.

a way that if two images (NC and FC conditions) were matched for luminance, it should be inconsequential whether the hues were natural or false.

As a result of the analysis conducted trying to assess the benefit of using color in object recognition, it can be concluded that both natural and false hue conditions resulted equally beneficial in the task accomplished during the experiment. There was no evidence of false color as a disruptive factor during this task, and both natural and false hue were similarly useful at different levels of image degradation. Thus, results indicate that participants conducted a bottom-up process during the object recognition task, making use of color (natural or false) only to achieve image segmentation. These findings are consistent with Wurm & Legge (1993), and Biederman & Ju (1988) views that primary access to object recognition uses structural (geometrical) representation of representation is in part generated by the presence of color. Participants did not use color to access stored knowledge of the object's psychological representation. If participants were taking advantage of natural color to achieve object recognition, the benefit of natural color should have been larger than the benefit of false color, because they would be able to fulfill a top-down and bottom-up recognition processes simultaneously.

More research must still be done in the field of human nighttime visual performance, based on the fact already stated that the benefits of integrating synthetic color to fused imagery is dependent on the color algorithm used, the visual task performed, and scene content (Steele & Perconti, 1997). Future research should study the benefits of using false color in each of these scenarios.

The results of this study give an indication that false color may be useful in future color fusion devices based on its facilitation of image segmentation with shape degraded images. Although this study was far from covering all different scenarios that may appear during a nighttime military operation, it shows as plausible to consider the use of synthetic color in the development of new military night vision devices.

THIS PAGE INTENTIONALLY LEFT BLANK

LIST OF REFERENCES

Adobe PhotoShop 4.0 Users Manual, Adobe Systems Inc., 1996.

Biederman, I. & Ju, G., "Surface versus edge-based determinants of visual recognition," *Cognitive Psychology*, vol. 20, pp. 38-64, 1988.

Brou, P., Sciascia, T.R., Lindeln, L., & Lettvyn, J.Y., "The colors of things," *Scientific American,* vol. 255(3), pp. 84-91, 1986.

Crowley, J.S., Rash, C.E., & Stephens, R.L., "Visual Illusions and Other Effects with Night Vision Devices," *Proceedings of the SPIE,* vol. 1695, pp. 166-180, 1992.

Derrico, J.B. & Buchsbaum, G., "A computational model of spatiochromatic image coding in early vision," *Journal of Visual Comunication and Image Representation,* vol. 2, pp. 31-38, 1991.

DeValois, R.L. & De Valois, K.K., "Neural coding of color"in *Handbook of Perception,* pp. 117-166, ed. E.C. Carterette & M.P. Friedman, New York: Academic Press, 1975.

De Valois, K.K. & Switkes, E., "Simultaneous masking interactions between chromatic and luminance gratings," *Journal of the Optical Society of America,* vol. 73, pp. 11-18, 1983.

Essock, E.A., Sinai, M.J., McCarley, J.S., & Krebs, W.K., "Perceptual ability with real-world nighttime scenes: Image intensified, infrared and fused-color imagery," *Human Factors, in press, 1999a.*

Essock, E.A., Sinai, M.J., McCarley, J.S., DeFord, J.K., & Srinivasan, N., *manuscript in preparation,* 1999b, "Human perceptual performance with nighttime imagery: Region recognition and texture-based segmentation."

Jameson, D. & Hurvich, L.M., "Essay concerning color constancy," *Annual Review of Psychology*, vol. 40, pp. 1-22, 1989.

Joseph, J.E. & Proffitt, D.R., "Semantic versus perceptual influences of color in object recognition," *Journal of Experimental Psychology: Learning, Memory and Cognition*, vol. 22, no. 2, pp. 407-429, 1996.

Kelly, D.H., "Spatiotemporal variation of chromatic and achromatic contrast thresholds," *Journal of the Optical Society of America,* vol. 73, pp. 742-749, 1983.

Krebs, W.K., Scribner, D.A., Miller, G.M., Ogawa, J.S., & Schuler, J., "Beyond third generation: A sensor fusion targeting FLIR pod for the F/A-18," *Proceedings of the SPIE-Sensor Fusion: Architectures, Algorithms and Applications II*, vol. 3376, pp. 129-140, 1998.

Krebs, W.K., McCarley, J.M., Kozek, T., Miller, G.M., Sinai, M.S., & Werblin, F.S., "An evaluation of a sensor fusion system to improve drivers' nighttime detection of road hazards," *Investigative Ophtalmology and Visual Sciences*, Suppl., in press, 1999a.

Krebs, W.K., Scribner, D.A., McCarley, J.S. Ogawa, J.S. & Sinai, M.J., "Comparing human target detection with multidimensional matched filtering methods," *Proceedings of the NATO Research and Technology Conference on Search and Target Acquisition,* Amsterdam, The Netherlands., 1999b.

Livingstone, M. & Hubel, D., "Segregation of form, color, movement, and depth: Anatomy, Physiology, and Perception," *Science*, vol. 240, pp. 740-750, 1988.

Maloney, L.T., "Color constancy and color perception: The linear models framework" in *Attention and performance XIV. Synergies in experimental psychology, artificial intelligence, and cognitive neuroscience,* pp. 59-78, ed. D.E. Meyer & S. Kornblum, Cambridge, MA: MIT Press, 1993.

Marine Corps Combat Development Center, *"Executive Summary of the F/A-18 Marine Corps T&R Conference Report,"* El Toro, CA; 1995.

Markoff, J.I, *Target recognition performance with chromatic and achromatic displays* (Research Rep. No. SRM-148), Minneapolis, MN: Honeywell, 1992.

Matlin, M.W. & Foley, H.J., *Sensation and Perception,* 4th ed., ed. Needham Heights, MA: Allyn and Bacon, MA; 1997.

MAWTS-1, Helicopter night vision device manual, *United States Marine Corps, Marine Aviation Weapons and Tactics Squadron One,* Box 99200, Yuma, AZ; 1995.

McDaniel, R., Scribner, D.A., Krebs, W.K., Warren, P., Ockman, N., & McCarley, J.S., "Image fusion for tactical applications," *Proceedings of the SPIE -Infrared Technology and Applications XXIV,* vol. 3436, pp. 685-695, 1998.

Mullen, K.T., "The contrast sensitivity of human color vision to red-green and blue-yellow chromatic gratings," *Journal of Physiology,* vol. 359, pp. 381-400, 1985.

Neitz, J., Neitz, M., & Jacobs, G.H., "More than three different cone pigments among people with normal color vision," *Vision Research*, vol. 33, pp. 117-122, 1993.

Ostergaard, A.L. & Davidoff, J.B., "Some effects of color on naming and recognition of objects," *Journal of Experimental Psychology: Learning, Memory and Cognition*, vol. 11, pp. 579-587, 1985.

Palmer, J., Ryan, D., Tinkler, R., & Creswick, H., "Assessment of image fusion in a night pilotage system," *NATO AC/243 Panel 3/4 Symposium on Multisensors and Sensor Fusion,* Brussels, Belgium, 1993.

Peli, T., Peli, E., Ellis, K., & Stahl, R., "Multi-Spectral Image Fusion for Visual Display," *Proceedings of the SPIE on Sensor Fusion: Architectures, Algorithms and Applications*, SPIE-3719, vol. 3, paper no. 44, (in press), 1999.

Perlmutter, M., “A developmental study of semantic elaboration and interpretation in recognition memory,” *Journal of Experimental Child Physiology,* vol. 29, pp. 413-427, 1980.

Polyak, S.L., *“The vertebrate visual system,”* Chicago: University of Chicago Press, 1957.

Price, C.J. & Humphreys, G.W., “The effects of surface detail in object categorization and naming,” *Quarterly Journal of Experimental Psychology: Human Experimental Psychology,* vol. 41(A), pp. 797-828, 1989.

Rabin, J. & Wiley, R., “Switching from Forward-Looking Infrared to Night-Vision Goggles: Transitory Effects on Visual Resolution,” *Aviation, Space, and Environmental Medicine,* vol. 65, pp. 327-329, 1994.

Salvendy, G., *“Handbook of Human Factors and Ergonomics,”* 2nd ed., ed. Wiley, 1997.

Sampson, M.T., *An assessment of the impact of fused monochrome and fused color night vision displays on reaction time and accuracy in target detection,* Master's Thesis, Naval Postgraduate School, Monterey, CA; 1996.

Schwarzkopf, H.N., *It Doesn't Take a Hero,* New York, NY: Bantom Books, 1992.

Scribner, D.A., Satyshur, M.P., & Kruer, M.R., “Composite infrared color images and related processing,” *Proceedings of the IRIS Specialty Group on Targets, Backgrounds and Discrimination,* 1993.

Scribner, D.A., Satyshur, M.P., Schuler, J. & Kruer, M.P., “Infrared Color Vision,” *IRIS Specialty Group on Targets, Backgrounds and Discrimination*, Monterey, CA; 1996.

Scribner, D.A., Warren, P., Schuler, J., Satyshur, M.P., & Kruer, M.P., “Infrared Color Vision: an approach to Sensor Fusion,” *Optics and Photonics News,* vol. 8, pp. 27-32, 1998.

Seymour, P.H.K., *"Human visual cognition,"* Collier MacMillan: London, 1979.

Sinai, M.J., McCarley, J.S., & Krebs, W.K., "Scene recognition with infrared, low light, and sensor-fused imagery," *Proceedings of the IRIS Specialty Groups on Passive Sensors,* Monterey, CA; 1999a.

Sinai, M.J., McCarley, J.S., Krebs, W.K., & Essock, E.A., "Psychophysical Comparisons of Single- and Dual-band Fused Imagery," *Proceedings of SPIE on Enhanced and Synthetic Vision, 3691*, Orlando, FL; 1999b.

Steele, P.M., & Perconti, P., "Part task investigation of multispectral image fusion using gray scale and synthetic color night vision sensor imagery for helicopter pilotage," *SPIE 11th Annual International Symposium on Aerospace/Defense Sensing, Simulation and Controls,* Orlando, FL; 1997.

Therrien, C.W., Scrofani, J., & Krebs, W.K., "An adaptive technique for the enhanced fusion of low-light visible with uncooled thermal infrared imagery," *Proceedings of the IEEE: International Conference on Imaging Processing,* pp. 405-408, 1997.

Toet, A., van Ruyven, L.J., & Valeton, J.M., "Merging thermal and visual images by a contrast pyramid," *Optical Engineering*, vol. 28, pp. 789-792, 1989.

Toet, A., & Walraven, J., "New false color mapping for image fusion," *Optical Engineering,* vol. 35(3), pp. 650-658, 1996.

Toet, A., Ijspeert, J.K., Waxman, A.M., & Aguilar, M., "Fusion of visible and thermal imagery improves situational awareness," *Proceedings of the SPIE Conference on Enhanced and Synthetic Vision*, SPIE vol. 3088, pp. 177-188, 1997.

U.S. Army CECOM Research, Development and Engineering Center, *"Night Vision and Electronic Sensors Directorate (NVESD),"* Fort Belvoir, VA;1997.

Vargo, J.T., *Evaluation of operator performance using true color and artificial color in natural scene perception,* Master's Thesis, Naval Postgraduate School, Monterey, CA; 1999.

Walls, G.L., *The vertebrate eye and its adaptive radiation,* Bloomfield Hills, MI: Cranbrook Institute of Science, 1942.

Waxman, A.M., Fay, D.A., Gove, A.N., Seibert, M.C., Racamato, J.E., Carrick, J.E., & Savoye E.D., "Color night vision: fusion of intensified visible and thermal IR imagery," *Proceedings on the SPIE Conference on Synthetic Vision for Vehicle Guidance and Control 1995,* SPIE vol. 2463, pp. 58-68, 1995.

Waxman, A.M., Gove, A.N., Seibert, M.C., Fay, D.A., Carrick, J.E., Racamato, J.E., Savoye, E.D., Burke, B.E., Reich, R.K., McGonagle, W.H. & Craig, D.M., "Progress on color night vision: Visible/IR fusion, perception and search, and low-light CCD imaging," *Proceedings on the SPIE Conference on Enhanced and Synthetic Vision 1996*, SPIE vol. 2736, pp. 96-107, 1996.

Waxman, A.M., Gove, A.N., Fay, D.A., Racamato, J.P., Carrick, J.A., Seibert, M.C., & Savoye, E.D., "Color night vision: Opponent processing in the fusion of visible and IR imagery," *Neural Networks,* vol. 10, pp. 1-6, 1997.

Waxman, A.M., Aguilar, M., Fay, D.A., Ireland, D.B., Racamato, J.P., Jr., Ross, W.D., Carrick, J.E., Gove, A.N., Seibert, M.C., Savoye, E.D., Reich, R.K., Burke, B.E., McGonagle, W.H., & Craig, D.M., "Solid–State Color Night Vision: Fusion of Low-Light Visible and Thermal Infrared Imagery," *Massachusetts Institute of Technology, Lincoln Laboratory Journal,* vol. 11, no. 1, pp. 41-57, 1998.

Wurm, L.H., Legge, G.E., Isenberg, L.M., & Luebker, A., "Color improves object recognition in normal and low vision," *Journal of Experimental Psychology: Human Perception and Performance*, vol.19, pp. 899-911, 1993.

INITIAL DISTRIBUTION LIST

No. Copies

1. Defense Technical Information Center..2
   8725 John H. Kingman Rd., STE 0944
   Fort Belvoir, VA 22060-6218

2. Dudley Knox Library..2
   Naval Postgraduate School
   411 Dyer Rd.
   Monterey, CA 93942-5219

3. Dr. William K. Krebs..3
   Operations Research Department (Code OR/Kw)
   Naval Postgraduate School
   1411 Cunningham Rd.
   Monterey, CA 93942-5219

4. Dr. Jason S. McCarley...1
   Beckman Institute
   University of Illinois
   405 North.Matthews
   Urbana, IL 61801

5. Dr. David H. Olwell...1
   Operations Research Department (Code OR/Ol)
   Naval Postgraduate School
   1411 Cunningham Road
   Monterey, CA 93942-5219

6. Naval Research Laboratory...1
   Dr. Dean A. Scribner
   Applied Optics Branch, Code 5636
   Washington, D.C. 20375-5000

7. LCDR Juan A. Aguilar, Spanish Navy..4
   Galileo, 93-3A
   Madrid 28003, Spain

8. Dr. Barbara O'Kane..1
Night Vision & Electronic Sensors Directorate
10221 Burbeck Road, AMSEL-RD-NV-MS
FT Belvoir, VA 22060-5806